The impact of effective factors on the Iranian electricity market in comparison to the Spanish electricity market

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Dedication

To my mother Ferdows Moravejolahkami and to my father Abbas Nasrazadani

To my siblings Mehdi, Bashir and Zahra

To my advisor professor Pilar Muñoz Gracia

To all people who positively impact on the world and human life

Human beings are members of a whole,
In creation of one essence and soul.
If one member is afflicted with pain,
Other members uneasy will remain.
If you've no sympathy for human pain,
The name of human you cannot retain!
(Sadi shirazi)

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Abstract

Due to the advantages of privatization, the Iranian government has taken certain fundamental steps in order to construct a competitive market, after passing the pertinent laws in its parliament as to the privatization of the electricity market. This PhD thesis presents a detailed econometric analysis of the Iranian electricity market by means of various approaches of time series analysis.

The analysis of an electricity market is useful in obtaining strategic market information on energy policy. The current study employs time series analyses to examine the policies implemented by the Iranian government towards a decentralized and competitive electricity market. As a benchmark for this kind of free market, and for the sake of comparison, the Spanish electricity market was chosen in order to conduct an analysis of both markets.

To carry out the modelling, two important factors—price and load—were chosen to assemble time series data from these markets. In following, statistical approaches to nonlinear time series will be used to illustrate the Iranian electricity market and help assess the behavior of these two main indices of the electricity market. The mechanisms of a developed market—Spain's—also provide an opportunity to express a comparison of the time series models used in these two, very different markets.

In this analysis of the energy, specifically electricity market, the researcher will investigate how load affects behavior patterns of price in both the Iranian and Spanish markets. This research will be quite helpful to establish the state of the Iranian electricity market and how exactly to stimulate its degree of competition. This part of the evaluation will also be performed using time series analyses.

In addition, the rate of change and market growth can usually be affected by fluctuating economic factors. Therefore, there will be an analysis of the impact of macro and microeconomic factors and indices on electricity prices in the Iranian market. The most important of these have been selected through the study and research of energy markets; the most significant include the Henry Hub Natural Gas Spot Price, Europe Brent Crude Oil Spot Price, the US dollar/Iranian Rial foreign exchange rate, and the Iranian (Tehran) Stock Exchange, specifically the TEPIX. Here, the aim is to survey the relationship between these factors and Iranian electricity prices via time series correlation analysis.

Forecasts will be performed to establish what might occur in significant indicators or factors of the electricity market. Here, the researcher will assemble this forecast from the best estimates derived from the study models and carry out simulations to further this aim. This short-term forecasting is applied to both Iranian and Spanish electricity prices and their respective loads.

The main idea of this thesis rests on the investigation of the state and degree of competition in the Iranian electricity market using the time series analysis approach. It consists of five chapters:

- Chapter 1 – This chapter consists of an introduction, in addition to the basic concepts and motivations. It also provides an outline of the thesis. The questions posed in this section of the thesis are analyzed during the literature review in the second chapter.

- Chapter 2 - Arranged in three sections, the first provides a background study to the thesis: the current state of the Iranian and Spanish electricity markets, including their growth and history, and also the structural framework of these markets. The importance of price and load in these markets will also be surveyed via their common and differentiating features. The second section describes the macro and microeconomic indices and factors having a significant impact on the electricity and energy markets. The impact of these factors on Iranian electricity prices—chosen according to the literary review—will be examined in detail. The third and final section of this chapter covers the background and literature related to these research methods, the perspective of which will be further defined and explained in the ensuing chapters.

- Chapter 3 - This chapter focuses on the approaches in time series analysis and time series modelling. Here, Iranian electricity prices (IEP), Iranian electricity loads (IEL), Spanish electricity prices (SEP) and Spanish electricity loads (SEL) are all closely examined using their respective time series. Consequently, this chapter is sub-divided into three sections: the first two establish data descriptions and propose estimated time series models. The first section strictly deals with daily IEP and IEL time series. The second section is devoted to the daily SEP time series. It also examines the two indices—price and load—of this market, also via the time series analysis approach. In these two initial sections, several time series estimation models are presented for each index. The sections are also dedicated to proposing and proving what the most suitable models are for each of the four time series. The models are further clarified through a residual analysis, and then compared according to Mean Square Error (MSE). Finally, the chapter's third section explores the role of load in each market, examining its impact on each market's electricity price using specific statistical methods such as scatter plots, etc.

- Chapter 4 - The aim of this chapter is to explore what relationship exists between certain micro and macroeconomic economic factors or indices, which were selected according to the literature review and the IEP and determine what impact these have, if any. Different approaches in time series analysis are utilized to examine this issue. In the second section of Chapter Four, forecasts are simulated in a similar manner as other recent studies, utilizing R packages, also described in this chapter. The most suitable model is then applied in order to estimate the forecast. This will be useful in accurately developing separate forecasts for each electricity market factor. These predictions are estimated from sampling the four selected time series: IEP, IEL, SEP and SEL time series.

- Chapter 5 - The final chapter includes the conclusions which are reached from all this research. Here, future lines of research are described and some complementary practical and theoretical aspects are presented in the Appendix.

Resumen

Analizar el mercado de la electricidad es muy importante para acceder a la información estratégica de dicho mercado que además puede ser empleado para aprobar las políticas energéticas. Debido a las ventajas de la privatización, el gobierno iraní ha tomado ciertas medidas fundamentales para construir un mercado competitivo, después de aprobar las leyes fundamentales en su parlamento que permiten la privatización del mercado eléctrico. Esta tesis doctoral presenta un análisis econométrico detallado del mercado eléctrico iraní, mediante diversos enfoques de análisis de series temporales. La idea principal de esta tesis se basa en la investigación así como el grado de consecución en el mercado eléctrico de Irán utilizando el enfoque de análisis de series temporales. En esta investigación se explican los mecanismos de mercado de la electricidad iraní mediante enfoques de series temporales lineales y no lineales. Los mecanismos que se han desarrollado con anterioridad en el mercado eléctrico español ofrecen la oportunidad de emplear el modelado de series temporales para comparar los dos mercados analizados como punto de referencia.Este estudio examina los dos índices –precio y potencia– de estos mercados mediante series temporales. A continuación, se comparan estas series temporales con el fin de presentar modelos para cada precio y potencia de dichas series temporales. Los modelos implementados incluyen: modelos lineales (ARIMA), modelos heterocedásticos condicionales (ARMA-GARCH) y modelos no lineales (SETAR y ARMA-TGARCH). Para evaluar el mejor modelo ajustado se calcula el error cuadrático medio (ECM) y se implementan los tests que permiten analizar la volatilidad residual. Suponiendo que nuestros datos detectan varianza condicional, la investigadora propone el modelo ARMA-TGARCH como el modelo más apropiado para el precio de mercado de la electricidad de Irán, modelo ARMA-GARCH para la potencia iraní y también para los precios y potencia de la electricidad española. Por último, esta investigación explora el papel de la potencia en cada mercado usando métodos estadísticos específicos, tales como gráficos de dispersión, etc. Este estudio será de gran ayuda para establecer el estado del mercado de la electricidad de Irán y cómo exactamente se puede estimular su grado de competencia. La investigadora sugiere, además, que en el estado actual, no existe una relación significativa entre el precio y la potencia en el mercado eléctrico iraní. Este resultado ha llevado a la investigadora a examinar el impacto de otros factores e índices macro y microeconómicos sobre los precios de la electricidad en el mercado de Irán. Los factores más importante han sido seleccionados a través del estudio y la investigación de los mercados energéticos; los más significativos incluyen el precio "Spot del Henry Hub Natural Gas", "Precio Spot del Petróleo Brent Europeo", "Dólar estadounidense / Rial iraní tipo de cambio", y la Bolsa de Valores (Teherán), en concreto el TEPIX. En este caso, el objetivo ha sido estudiar la posible relación entre estos factores y precios de la electricidad de Irán a través de la correlación de series temporales. La investigadora también ha reunido las predicciones de las mejores estimaciones derivadas de los modelos estudiados y ha llevado a cabo simulaciones para desarrollar modelos de predicción. Finalmente, considerando los resultados obtenidos a través de los testes y análisis de datos que examinó el mercado de la electricidad de Irán, se concluye que el mercado de la electricidad de Irán podría ser aún reconocido como un mercado no libre / centralizado cuestionando las políticas reclamadas hasta ahora implementadas hacia la descentralización y la privatización del mercado iraní.

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Acronyms

ACF……………………………………………………………………..……………………..…….Autocorrelation function.
ADF……………………………………………………………………………………......Augmented Dickey Fuller Test.
APARCH...Asymmetric Power ARCH model.
ARIMA……………………………………………….Autoregressive integrated moving average model.
ARIMAX……………………………………………..…Autoregressive Integrated Moving Average with Explanatory Variable Model.
ARMA……………………………………………………………Autoregressive-moving-average model.
B.E. oil spot price…………...Europe Brent oil spot price.
CCF………………………………………………………………..……………............Cross correlation function.
Diff (d1/d7)……………………………………………………………………………………taking difference.
EBSP …………………..Europe Brent oil spot price.
GARCH………………………………………………………………Generalized Autoregressive Conditional Heteroskedastic model.
GSgarch.Sim……………………………………………………………............................library (fGarch) in R.
H.H gas spot price……………………………..............................Henry Hub natural gas spot price.
HEGY test………………………………………………………………………........Seasonal unit root Test.
HHSP…………………………………………..….............................Henry Hub natural gas spot price.
IDEX…………………………………………………….................USdollars/Iranian Rials exchange rate.
IEL……………………………………………………………………….Iranian electricity load time series.
IEP……………………………………………………………..................Iranian electricity price time series.
IID……………………………………………....................Independently and Identically Distributed.
Log………………………………………………………...logarithm.
MIBEL…………………………………………………………..……………….....Spanish electricity market.
MSE ……………………………………………………….…………….Mean Square Error MSE Test.
PACF…………………………………………...Partial correlation function.
R…………………………………………………………………………………..……………........Soft ware R.
Robust cor ………………………...Robust correlation.
SARIMA………………………………….Seasonal autoregressiveinteg rated moving average model.
SARMA-SGARCH……………………………………………Seasonal autoregressive-moving-average - Seasonal conditional heteroskedastic model
SAS…………………………………………………………………………………………...........Software SAS.
SEL…………………………………………………..……................Spanish electricity load time series.
SEP………………………………………………………..……….……Spanish electricity price time series.
SETAR………………………………………………….Self-Exciting Threshold Autoregressive model.
TAR………………………………………………………................................Autoregressive threshold model.
TEPX……………………………………………………..............................Tehran stock exchange price index.
USD/IRR exchange rate……………………………….…………….USdollar/Iranian Rials exchange rate.

Chapter One:
Introduction

1 Introduction

Iranian government organizations are currently trying to change the country's electricity market through privatization (Khalili and Mehri, 2007). Due to the advantages of the liberalization of their respective electricity markets, the United States and several European countries have also applied certain developed management systems to improve their markets(see Muñoz, Heredia and Corchero (2013); Corchero(2010); Weron(2007)). Nowadays, these countries can be viewed as benchmarks and highly-developed models for other countries seeking strategies for improving their own electricity markets (Kotler and Armestrong, 2010; Weron, 2007). One of these that could be considered a benchmark is the Spanish electricity market.

This trend toward competition has had vastly different outcomes on economic activities, such as developing decision support system models in energy market management (Finn, 2000; Sioshansi, 2008; Ventosa et al., 2005). According to some studies, due to the restrictions and limitations in the Iranian electricity market, the competitive market is only conceivable in certain hours, while in the remaining hours some pivotal suppliers abuse the market situation and exercise market power during special and off-peak hours (Asgari and Monsef 2010). In other words, the mere launching of an Iranian electricity market does not mean that it will be introduced as a competitive market (Bigdeli and Afshar, 2009).

According to various approaches in market management, in order to create and sustain a market, it is essential to investigate a known market—a model—and make a strategic analysis in order to predict the behavior of the new market (Kotler and Armestrong, 2010). Here, one question arises, that must be addressed: is it possible to describe the behavior of the Iranian electricity market? More knowledge must be attained about its behavior using certain critical elements and factors in this market, such as price or load.

Various studies have been published which concentrate on these issues and propose economic methods to forecast such indices. Most of these studies, however, only focused on describing the methodology. Therefore, this paper—through a different viewpoint of this market—aims to conduct a comprehensive analysis of this market by examining behavior patterns of price and load, using various approaches in time series analysis.

The theory and application of time series analyses have developed rapidly since their introduction in 1970 thanks to the ground-breaking work of Box and Jenkins (see Box, Jenkins and Reinsel (1994); West et al.(1994); Box et al.(2008); Hu (2011)). This progress was made in expanded time series models such as the "autoregressive integrated moving average", ARIMA model, the "Generalized Autoregressive Conditional Heteroskedastic Model", GARCH models, as well as the nonlinear Self-Exciting Threshold AutoRegressive (SETAR) model and so on, for more information, see, Armstrong (2001); Hu (2011); Makridakis and Hibon (1997); Box, Jenkins and Reinsel (1994); Brockwell and Davis (2006);Wurtz et al.(2006).

However, the importance of price leads to the examination of what role other important macro and microeconomic factors—economic indices, for example—are playing in the Iranian electricity price. The results of these studies are made clear via certain time series statistical methods, such as scatter plots, Pearson correlation methods, and etc. The research presented in following provides short-term forecasts for Iranian electricity prices (IEP), Iranian electricity loads (IEL), Spanish electricity prices (SEP) and Spanish electricity loads (SEL). These forecasts will provide accurate estimates on future prices and loads in these markets, and are useful in finding out more information about the behavior patterns of these significant elements in both markets.

In general, the second chapter of the thesis is related to the current state and the background of the methodology employed in this research, while the third chapter of the research provides a data description using the time series statistical methods. It surveys four time series taken for the IEP, SEP, IEL and SEL. The third chapter goes on to investigate a valid model for each time series according to different approaches in time series modelling, such as the ARIMA and ARMA-GARCH models, etc. Finally, the chapter explores the relationship between the indices of price and load is also examined in these two markets.

The fourth chapter researches the kinds of relationship between the IEP and macro and microeconomic indices such as Henry Hub Natural Gas Spot Price, the Europe Brent Spot Price, the US dollars/Iranian Rials foreign exchange rate, and the Iranian (Tehran) stock exchange, specifically the TEPIX, all of which had been thoroughly explained in the literature review in Chapter Two. The fourth chapter also includes a short-term forecast for the IEP, IEL, SEP and SEL in order to provide an accurate estimate of price and load in an immediate future of 14 days.

The last chapter, Chapter Five, contains the conclusions of this study based on the main questions posed by the thesis. However, it is hoped that the findings of the current research can be employed to improve market efficiency management, provide knowledge and better estimates of market behavior for future planning. This research, clearly, will be useful towards developing and implementing the appropriate statistical methods to make more exact estimates of the future behavior of Iranian electricity market according to its more influential indices, such as the analysis of price and load. It also provides for the possibility of having more accurate predictions for prices and loads in both the Spanish and Iranian markets. In the future, this research will attempt to introduce advanced models using time series approaches by which there can be a more accurate analysis of the (Iranian) electricity market.

1.1 Motivations and purpose

The advantages of a competitive and liberalized market have led most countries to switch their electricity markets from a monopoly with state-owned companies to a competitive market and privately-owned companies. Iran has also engaged in this challenge of how to change its electricity market. On the other hand, the developed management systems of the Spanish electricity market (MIBEL) have led the researcher to considering it as a suitable benchmark and a pattern for the developed market. An appraisal therein would be useful in understanding how to develop suitable strategies for increasing competition in the Iranian electricity market.

Due to certain restrictions, such as a lack of information and the current state of market power in Iranian electricity market, where certain pivotal suppliers abuse their market position and exercise their power over the market (Asgari and Monsef, 2010), it seems that what competition there is in this market is formed during certain off-peak hours. On the other hand, factors such as international sanctions have long redefined the Iranian economic market, especially the energy sectors (Khalili and Mehri, 2007). Yet another important issue is the role the Iranian government plays, being the primary owner of large swathes of the energy industry, such as Iran's oil and gas industry (Cavendish, 2007; USA IBP, 2009). The country's *Ministry of Energy* controls the electricity sector and energy efficiency policies (Enerdata, 2014).

In general, the rate of market growth and change can be affected by a variety of factors, economic and otherwise. For example, Aggarwal et al. (2009) and Le and Vinh (2011) point toward the impact of inflation on a country's economy. The price of energy is another important factor mentioned in several studies—such as oil prices (Brown and Yücel, 2002; Farzanegan and Markwardt, 2009) and gas prices (Asafu-Adjaye, 2000; Emery and Liu, 2002; Moutinho,et al., 2011; Le and Vinh, 2011; Boqiang and Dunguo, 2008). The exchange rate also plays a significant role in economic activities (see Yu and Mallory, 2013; Sameti, 2008; Adaramola, 2011; Cong et al., 2008). But economic indicators may not be the only factors having an impact on the progression of the Iranian market. Therefore, in order to investigate this issue in the Iranian electricity market, one motive of the research is to evaluate the role of some these important economic factors in the Iranian electricity market.

Accordingly, the researcher employs time series analysis models of this market. These studies are made in order to examine the effective indices of the electricity market. On the other hand, the developed systems of management in the Spanish electricity market (MIBEL) leads to its consideration as a benchmark and a model of a developed market. Such an appraisal is useful towards understanding how to prepare suitable strategies for increasing competitive performance in the Iranian electricity market.

Furthermore, the importance of two factors—the indices of price and load—of electricity markets have pointed towards the need for an evaluation of their role in both markets under study (Weron, 2007). Subsequently, there is cause to contrast their behavior via different approaches of time series analysis, such as linear and nonlinear modelling. According to certain management methods used in developed market, used for creating and capturing market share, it will necessary to make a strategic analysis in order to ascertain market behavior. After that, there must be knowledge as to what elements, factors and behavior patterns therein affect the market (such as price, demand, etc).

Overall, with the consideration of several studies, it could be said that most of these solely focus on the forecasting of price estimation models. They concentrate on recent price performance and do not consider hypothetical indices and macro and microeconomic factors which may affect the market. Therefore, this PhD thesis provides for this possibility by analyzing the impact of these factors on Iranian electricity prices.

This research will assist in the development and implementation of some statistical methods to provide a suitable estimate of future Iranian electricity prices and loads. The importance of this project rests on the fact that it will help to provide more knowledge about the Iranian electricity market and its significant indices or factors. This electricity market analysis will also be useful for market managers, for example, in how to improve the use of renewable energy and energy-efficient technologies in the electricity marketplace. The strategic information derived from this research will be helpful to the Iranian government and beneficiaries that "are interested in the rapid growth of the electricity market" (Logan, 2015). In short, the research can be of great assistance in improving efficiency and providing more strategic knowledge about the future of this market for decision makers. In addition, its findings can be employed to improve efficiency management in the Iranian and Spanish electricity markets and to provide knowledge and better estimates of the behavior of these energy markets for purpose of future planning.

In conclusion, this doctoral thesis aims to explore the possibilities of statistical, mathematical and market procedures in solving the previously described problem.

1.1.1 Main objectives of research

Overall, the main objectives of this PhD thesis are:

- To make an in-depth study of the Iranian electricity market and to compare it with one of the European electricity markets. Here, the Spanish market (MIBEL) is examined as a developed market.
- To investigate the role of two important elements—price and load—in the Iranian and Spanish electricity markets, which implies a full analysis that must be made with these factors and indices.
- To evaluate the role and relationship of macro and microeconomic indicators such Tehran stock exchange, the USD/IRR exchange rate, the Henry Hub Natural Gas Spot Price and the Europe Brent Spot Price in establishing market prices.
- To provide a short-term forecast of the Iranian electricity market in comparison with the Spanish electricity market according to their most significant indicators, price and load.

1.2 Outline of the thesis

The literature and studies related to the research are reviewed in Chapter 2. Section 2.1 introduces the Iranian electricity market, exploring its history and market pricing structure. Section 2.3 follows with a similar description of the Spanish electricity market. Both these sections contain some structural comparisons of these markets. In section 2.2, the importance of price and load in other electricity markets as explained by other recent studies and literature will be provided.

Afterwards, some main macroeconomic and microeconomic factors and indices having a strong impact on electricity markets will be given a general overview in Section 2.4. The review of other studies have led to the use of the Tehran Stock Exchange index, USD/IRR exchange rate, Europe Brent oil prices, and Henry Hub natural gas prices as significant economic indices in the research. These are introduced as the most important factors influencing energy markets and the Iranian electricity market in the research; Sections 2.4.1, 2.4.2 and 2.4.3 provide further explanation on their importance to this research.

Section 2.5 contains a background of the methods used in this thesis. What is more, these methods and the importance thereof are briefly expanded upon by means of other studies; in the following chapter, the details of how these methods are specifically employed in this research are provided.

Chapter 3 focuses on the approaches used in the time series modelling. Sections 3.1, 3.2, 3.3 and 3.4 of the thesis deal with a market analysis of the Iranian and Spanish electricity time series. In the first of these parts, specifically in Sections 3.1.1, 3.2.1, 3.3.1 and 3.4.1, a data description of each time series is given, introducing the analysis approaches used in the thesis concerning the IEP, IEL, SEP, and SEL, respectively. After the data description, the following Sections, 3.1.2, 3.2.2, 3.3.2 and 3.4.2 contain the time series analysis modelling for each of these time series. In each there is an attempt to estimate the most suitable model for the time series using linear and nonlinear time series modelling approaches. The estimated time series models for Iranian electricity prices are given in Sections 3.1.2.A. (ARIMA model), 3.1.2.B (nonlinear estimated model – SETAR), 3.1.2.C (ARMA-GARCH model), 3.1.2.D (ARMA-TGARCH model), 3.1.2.E (ARMA-TGARCH model after de-trending the time series) and 3.1.2.F (APARCH model).

The first ARIMA model (a classic time series model) is represented because there is no stationary behavior in this time series. Considering the behavior of the time series (using nonlinear time series analysis approaches), two SETAR time series models are estimated for the IEP. The volatility in the IEP time series pointed toward the use of the ARMA-GARCH model. In addition, the nonlinear behavior of this time series and existence of breakpoints in the resulting data led the researcher to employ the ARMA-TGARCH models. Here, due to the influence of information on electricity market pricing, the APARCH model was evaluated for the IEP time series.

As for the IEL time series, Sections 3.2.2.A (ARIMA model and SARIMA model), 3.2.2.B (ARMA-GARCH model after taking into account seasonal differences in the time series), and 3.2.2.C (ARMA-GARCH model after seasonal and first-order differences in the time series) reflect the models estimated using linear and nonlinear analysis approaches.

The estimated models for the SEP price time series are represented in Sections 3.3.2.A (ARIMA model), 3.3.2.B (ARMA-GARCH model) and 3.3.2.C (SARMA-SGARCH model). Meanwhile, Sections 3.4.2.A (ARIMA model), 3.4.2.B (ARMA-GARCH model) and 3.4.2.C (SARMA-SGARCH model) present the estimated models for the SEL time series.

In order to choose the most suitable models for the time series, Sections 3.1.3.A, 3.2.3.A, 3.3.3.A and 3.4.3.A contain a comparison of each of these models. Then, in Sections 3.1.3.B, 3.2.3.B, 3.3.3.B and 3.4.3.B, there is an attempt to confirm the validation of the models using an in-sample prediction of the time series.

Section 3.5 of Chapter 3 illustrates the impact that pricing loads have on the two markets using scatter plots in Section 3.5.1, cross correlation functions in 3.5.2 and the rational distributed lag model in 3.5.3.

Chapter 4 explores the relationship between Iranian electricity prices and the four previously mentioned economic factors using statistical methods such as Pearson's correlation coefficient method, scatter plots of each factor, and robust correlation in Section 4.1.2. Sections 4.1.1.A, 4.1.1.B and 4.1.1.C examine the kind of relationship existing between these economic factors using the aforementioned statistical methods, with the aim of examining the possibilities of estimating what models of regression exist between them, if any.

Finally, Chapter 5 presents the conclusions of the thesis and future lines of research, in addition to some complementary appendices.

1.3 Questions of research

The questions this thesis poses include:

- Is it possible to define the Iranian electricity market as a liberalized and (perfectly) competitive market in comparison with other developed electricity markets such as the Spanish electricity market?
- How do Iranian electricity prices and loads, as two important indices and elements, behave in the electricity market in comparison with the behavior of these factors in the Spanish electricity market (used as a benchmark)?
- What are the roles of important macro and microeconomic factors in the Iranian electricity market? What kinds of relationships exist among them?
- Is it possible to present a short-term forecast for prices and loads in both of these electricity markets?

Chapter Two: Literature Review; Research History and Background

2 State of art

The literature related to this study represents the history of two markets: the Iranian electricity market and the Spanish electricity market. Here, the structures of these markets are described via other studies and research. These clarify the importance of analyzing the impact of certain factors or indices on energy and electricity markets, such as load and price. The literature also briefly compares the structures of the two electricity markets and the main idea of this study is formed according to these investigations. The background to the research is shaped by the books, articles, etc., which are related to these markets and the main idea of this thesis. This chapter goes on to select the most important macro and microeconomic factors having an impact on energy markets, especially the Iranian electricity market. This section is completed by the examination of several studies. The final section of this chapter is devoted to the background of the methodology used in this research.

2.1 Iranian electricity market

The electricity industry first came to Mashhad, Iran in 1901. At that time, there was no official independent body in charge of managing electricity-related affairs, and one would not exist until 1969 (Tavanir, 2011a). Due to the "increased demand for electricity", "the need to organize the budget" and the "plan to generate and regulate the size of production", the Iranian government established the "Iranian Organization for Electric Power Affairs" (Tavanir, 2011a; Riahi and Afshar, 2009). The rapid development of the electric power industry in Iran led to the idea of establishing a "Ministry of the Water and Electric Power Supply". This ministry, with this rather lengthy name, was finally established in 1965 (Tavanir, 2011a; Riahi and Afshar, 2009). The ministry also set up regional electric companies in order to manage power grids across the country. In 1969, the "Tavanir Company" undertook the task of managing and improving electric power generation and transmission, as well as wholesaling electricity retailing to the regional utilities (Tavanir, 2011a). The responsibility for the "country's energy plan" was completely given over to the "Ministry of the Water and Electric Power Supply" in 1974. In addition, it was also allocated the task of developing gas and nuclear production programs. At that point, the name of the ministry was changed to "Ministry of Energy" (Riahi and Afshar, 2009).

In the years that followed, the Tavanir Company experienced changes to its authority, and also after the Islamic Revolution of Iran. The Tavanir Company was restructured twice, once in 1989 and another time in 2001 (Riahi and Afshar, 2009; Tavanir, 2011a). It was renamed the "Iranian Organization for the Management of

Electric Power Generation and Transmission (Tavanir)". Consequently, the deputy minister's authority for all electricity-related affairs was given over to this body, whose current organizational structure manages the generation, transmission and distribution of electric power in Iran (Tavanir, 2011a; Riahi and Afshar, 2009). On the other hand, in order to develop energy policy and manage industry operations, certain sections of its authority were redefined (Asgari and Monsef, 2010; Tavanir, 2011a; Riahi and Afshar, 2009). The ministry transferred the management of the 16 Regional Electric Companies (RECs) to the Tavernier Company as well as the 32 Generation Management Companies (GeMCs), 42 Distribution Companies, the Iranian Power Development Company (IPDC), the Renewable Energy Organization (SANA), the Energy Efficiency Organization (SABA), the Power Plant Project Management Company (MAPNA) and the Power Plant Repairs Company (Asgari and Monsef, 2010; Tavanir, 2011a).

All of these changes were based on the new interpretation of Article 44 Iran's constitution for more information, it is suggested to read Asgari and Monsef (2010). "According to Article 44, large-scale, primary industries such as 'electricity supply' are publicly owned and are administrated by the State" (Asgari and Monsef, 2010). According to the traditional overarching interpretation of this article, all areas of the electricity generation industry must be state-owned. But the words of the law indicating "electricity supply" opened the way for a revised interpretation by which the "supply" is meant as "be sure from supplying the generation" (Asgari and Monsef, 2010; Ghazizadeh et al.,2007). The new reading paved the way for the following legal actions, aimed at reforming Iran's power industry, which are summarized in Table 2.1; see Asgari and Monsef, (2010).

Table 2.1: Legal actions taken to restructure the Iranian power industry.

No.	Title	Objective
1	Article 122 (sub-article b) of the III Socio-Economic Development Plan.	Provide the legal foundation for private sector participation in the country's power industry.
2	Article 20 of the IV Socio-Economic Development Plan and its code of practices.	Encourage private sector investment in the power projects.
3	Article 25 (sub-article b) of the IV Socio-Economic Development Plan and its code of practices.	Provide open, indiscriminate access to the transmission network.
4	Sub-Article L of Section 21 of the 2003–2004 Budget Act.	Attract and support private sector investment in the power industry.
5	The 2005–2006 Budget Act.	Attract and support private sector investment in the power industry.
6	Law on the Independence of Distribution Companies.	Provide for the transfer of distribution sector activities to private companies.
7	Ministry of Energy notice on conditions, rating and procedure for the purchase and sale of power, and further amendment.	Determine the executive framework for electricity transactions and power transmission.
8	General policies of Article 44 of the constitution of the Islamic Republic of Iran.	Resolve legal barriers, provide for the foundation of the private sector, there in accelerating the transfer of state authorities.

At the present time, competition in deregulated electricity markets has given rise to many opportunities worldwide, bringing not only such advantages as cheaper electricity to the end consumer, but also improved technological equipment, increased reliability, fewer situations of overcapacity, as well as leading to greater efficiency in power generation, transmission and distribution services (Asgari and Monsef, 2010; Weron, 2007; Muñoz et al, 2013; Corchero, 2010). Overall, the trend toward competition has had vastly different outcomes in terms of economic activity, such as developing decision-making and supported models in energy market management (Finn, 2000; Sioshansi, 2008; Ventosa et al., 2005).

Consequently, such benefits have encouraged other electricity markets to progress towards a market competition model. Spain's electricity market (OMEL), one of our examples, underwent several structural changes in order to become a developed competitive market. The reform of the Spanish electricity market has several aims: "to guarantee the supply of electricity, the quality of this supply and to guarantee this process at a lower cost. Also, to define a transient process for the liberalization of retail supply in this market" (OMEL website, 2010; Muñoz et al, 2013, Corchero, 2010).

In contrast with developed markets, there are others that despite having the sufficient capacity and infrastructure to become competitive markets, their progress in this transformation towards a free market is extremely slow.

"The ideas behind spurring on privatization and competition environment in the Iranian electricity industry include: to reduce the government's responsibility and monopoly of this market; to separate and classify the costs of generation, transmission and distribution in the electricity market; to provide essential facilities for direct and fair trade, and encourage competition amongst market beneficiaries; to improve productivity and reduce losses, consequently lowering power generation costs; to increase the international stature of this market; and to develop the domestic construction, transmission and distribution of power plants" (Asgari and Monsef, 2010). However, the emergence of an Iranian electricity market took over 100 years—from the time that this industry came to Mashhad, Iran in 1901 (Tavanir, 2011a) until it was launched on 23 October 2003 (Asgari and Monsef, 2010; Tavanir, 2011a). Such a slow rate of growth may be due to Iran's economic policies, which are becoming more and more politically-based (Mazarei, 1996; Khalili and Mehri, 2007).

Generally-speaking, these transformations have convinced the Iranian ministry to give up the centralization model. To do so, it has been trying to establish the fundamentals of a competitive and private market (Asgari and Monsef, 2010; Tavanir, 2011b; Khalili and Mehri, 2007).

In recent years, monopolies have found it increasingly difficult to retain exclusive market share, which is likely to create competition among free market beneficiaries (see Muñoz, Corchero and Heredia, 2013; Weron, 2007). In general, a competitive market framework with power suppliers (Gen.COs) and distributors (Dis.COs) tends to fosters profit maximization. These companies also improve their technical equipment and management systems in order to decrease their cost margins

(Muñoz et al.,2013; Corchero, 2010); the end result is improved capacity. In addition, they also need to make accurate forecasts regarding market capacity in order to produce electricity at the lowest price. Consequently, the end consumer receives cheaper electricity from the distributors (see Muñoz, Heredia and Corchero, 2013; Weron, 2007). On the other hand, the amount of available electricity increases, due to more competition among suppliers, especially at peak times (Weron, 2007).

Recently, an important issue has arisen regarding how prices are determined in the electricity pools. One of the main concerns in the Iranian electricity market is that a "market power" situation exists, similar to that of a mandatory pool (Asgari and Monsef, 2010). In other words, a company with market power, perhaps a retailer or consortium of retailers, is defined as one owning the utility in order to drive the spot price above a competitive level, control the total output, or exclude competitors from a sizeable market for a significant period of time (Asgari and Monsef, 2010).

The pool can also be defined as an "e-commerce market place entailing a framework enabling physical bilateral contracts" (Bigdeli and Afshar, 2009).

In the pool, power suppliers and distribution companies submit their bids based on the generation, consumption and transmission services to the Market Operator (MO). The MO then uses a market-clearing tool to set the market price. This is normally based on single-round tendering" (Bigdeli and Afshar, 2009; Asgari and Monsef, 2010).

Electricity markets use several mechanisms to determine prices, such as uniform pricing (UP) and pay-as-bid (PAB) (Bigdeli et al., 2009; Bigdeli and Afshar, 2009; Weron, 2007; Asgari and Monsef 2010). In the UP mechanism, the market-clearing price is paid to every winning bid. In the PAB structure, every winning bid receives its price as income. Hence, having the right bidding strategy is critical to maximizing profits in an electricity market. It goes without saying that bids should be determined according to market price indices (Bigdeli and Afshar, 2009).

However, the Iranian electricity market uses a pay-as-bid mechanism with a unilateral tendering process. Iranian electricity prices are also determined by the "hourly accepted weighted average price" or WAP (Bigdeli and Afshar, 2009). This is the consequence, as explained above, of the influence of the market power. Consumers and producers—as in the mandatory pool state—have to send their bids to an Independent System Operator (ISO) before the market is shared amongst the beneficiaries; What is more, regional electric companies (RECs) are only entitled to forecast their demand hourly, which means that the demand curve shows a vertical line at a certain hour. Finally, there are the seven experts chosen by the Iranian energy minister (MOE) in charge of monitoring the market. They provide a close and effective supervision on the power market of the country as a "Electricity Market Regulatory Board" (Asgari and Monsef, 2010).

In reality, the Iranian electricity market is a hybrid market model in which the suppliers and the consumers have access to all information, with the exception of the price (Asgari and Monsef, 2010). In other words, companies to some extent have power over pricing, depending on their size, as well as access to market information (Asgari and Monsef, 2010; Bigdeli and Afshar, 2009). The general features of the Iranian electricity market mainly consist of: a day-ahead market, unilateral tenders, discriminatory supply side pricing, PAB, wholesale markets and demand side uniformity (market clearing prices) (Asgari and Monsef, 2010; Bigdeli and Afshar, 2009; Bigdeli et al, 2009).

Annual reports on the performance of Iranian electricity industry (2010-2011) indicate certain sections have indeed improved (Tavanir, 2011b). This assessment is based on the aforementioned legal structures that were enacted in regards to market privatization (Asgari and Monsef, 2010). Furthermore, the Iranian government has carried out certain fundamental technological measures in order to move towards a competitive electricity market. Nevertheless, some obstacles and restrictions remain in this goal to form such a market in Iran.

Competition in the true sense of the word is only conceivable in certain off-peak hours. These restrictions range from the lack of appropriate measurements, communications and telecommunication infrastructure to the malfunction of power stations, transmission network constraints, power supply shortages, market power issues, and so on (Asgari and Monsef, 2010). What is more, some pivotal suppliers benefit from their market status to obtain a greater share of the power market.

In addition of these limitations, the political climate with regard to Iran's economy has affected the growth of the domestic electricity market (Mazarei, 1996; Khalili and Mehri, 2007; Behboudi et al., 2014). Several other factors, such as international sanctions or the Iranian nuclear crisis, have also shaped the economy, and the energy market in particular (BBC News-Middle East, 2015; Monshipouri and Dorraj, 2013; Peterson, 2012).

To conclude, all these conflicting issues point toward the need for an in-depth study of the market and its most important components, and compare them with other competitive markets, such as Spain electricity market. We are now faced with a question: is it possible to describe the Iranian electricity market as a liberalized or competitive market, based on the scale of its infrastructure and fundamental legal structure?

2.2 The importance of electricity price and load

Different features of the Iranian electricity market raise the question expressed in the previous paragraph. To answer this, the research will now turn to the market mechanisms themselves.

According to the principles of "market management", in order to truly understand a given market, it is worthwhile procuring knowledge about its components, such as price and load (demand), etc. In other words, "electricity market analysis will be a practicable and ideal guide for all strategic planners, market analysts, and marketing researchers in this sector of the energy market" (Stevens, et al., 1993). How elements perform can also influence market pricing strategies (Kotler & Armstrong 2013a; Weron

2007; Nicholson & Snyder 2011).This means "if a company plans to sell its products or services in international markets, research on the factors in each market must be analyzed before setting their prices" (Tanner and Raymond, 2001; Kotler and Armstrong, 2013). Overall, electricity-related facets (such as storage, low-tension, high seasonal demand and existing price volatility) clearly affect price estimates, making such practices quite risky and it is introduced as the most important issue for the electricity market (Bigdeli et al., 2009).

To do this, several studies focus on energy market analysis, putting forth various economic methods and forecast models to estimate the behavior of the electricity market and prices (Bigdeli et al., 2009; Safakish and Manzur, 2009) :

- Woo et al. (2003) presented an analysis of electricity market reforms which has already taken place in the UK, Norway, Alberta (Canada) and California (USA). Their paper "explains why an electricity market reform can easily fail to deliver the promised gains of better service at lower and more stable prices".
- Rodriguez et al. (2004) investigated the competitive power system market of Ontario using artificial intelligence methods for forecasting energy prices.
- Ventosa et al. (2005) focused on trends in electricity generation markets and modelling, going on to explain that a reform of this kind of electricity market can be extremely risky.
- Conejo et al. (2005) provided a forecast for 24 energy market-clearing prices using time series, networks and wavelet analysis. The techniques employed in the time series procedures were comprised of ARIMA, dynamic regression and transfer function.
- Lora et al. (2007) presented a simple technique for forecasting next-day prices by weighting the methodologies used by nearby markets.
- Safakish and Manzur (2009) used ARIMA and GARCH models in order to forecast and estimate Iranian electricity market prices using the time series modelling approach. However, their studies provide no explanation of the degree of market competition.
- Mazengia and Tuan, (2008) wrote an article about spot price forecasting using time series models for the Nord Pool electricity market.
- Ghadrei and Nokhandan (2009) and Pao (2007) proposed a highly-accurate short-term neural network model for forecasting prices.
- Amjady et al. (2010) also presented an electricity price forecast using modified relief algorithms and hybrid neural network.
- Zarezadeh et al. (2008) confirmed the methods of the "artificial neural network" to perform better in comparison with traditional electricity forecasting methods.
- Bigdeli and Afshar (2009) described the Iranian electricity market according to the focal point of its pay-as-bid mechanism.

- Bigdeli et al. (2009) concentrated on the use of the price and load as indices to analyze the behavior of the Iranian electricity market.
- Asgari and Monsef (2010) research the Iranian electricity market by comparing two scenarios—the current situation and future outlook of the ownership of the generation sector in Iran's power industry—in order to analyse the intensity of competition in Iran's electricity market and examine whether this market is functioning at an appropriate level of efficiency.

It cannot be overstated that the analysis and forecasting of electricity prices is extremely important to all market players in the short, medium and long term (Benini, et al., 2002). The consideration taken from these studies is that most solely rest their estimates on the performance and forecast of market prices. Their market analyses are produced without the observation of what role other factors may play in this particular energy market (Weron, 2007; Kotler and Armstrong, 2013), or their effect on market analysis and price forecasting. It is critical, for market planners to take into account other elements—such as load—which may end up modify pricing policies and strategies in a (competitive) market (Bunn 2004; Weron, 2007; Nicholson and Snyder, 2011). In addition, basic economic theories explain that price patterns according to demand is predictable in competitive markets (Nicholson and Snyder, 2011). Logically, a relationship exists between price and load in liberalized markets (see Weron, 2007; Nicholson and Snyder, 2011). In other words, variations in load alters prices in a competitive electricity market (Weron, 2007). The importance of this index has been made clear in several studies on the load in this energy market:

- Vilar, et al. (2012) found forecasts on electricity demand and price key factors in Spain's competitive electric power market.
- Ahmari et al. (2005) improved their research of Iran's electricity market by means of dividing the price of electricity into two major sections: one section relating to demand and the other to the behavior of market players. However, both sections evaluated the predictability of electricity prices in the face of these separated components. Their studies also remarked on the importance of the size of demand (or load) in this market.
- Barforoushi et al. (2006) focused on load to present a plan for the Iranian electricity market.
- Afshar and Bigdeli (2011) considered short-term load forecasting for the Iranian electricity market using a singular spectral analysis.

Most of these studies investigated load as demand and none in consideration to electricity prices. There are some smaller studies that present long-term approaches for load in order to make forecasts (see Hyndman and Fan, 2010).

In conclusion, most of these market studies only described methodology approaches, especially with regard to the Iranian electricity market. They only present technical surveys to explore its mechanisms. Therefore, this study takes into account both Iranian electricity market prices and loads in order to find the answer to the primary question of the research, which will be done by examining the relationship between these two factors.

2.3 Spanish electricity market

Since the late 1980s, policy makers and regulators in a number of countries have liberalized and deregulated their electric power sectors (Sioshansi, 2008). Weron (2007) explained that "Power market liberalization was pioneered by Chile for the first time. This reform, which began in 1982, was based on the idea of separate generation and distribution companies where power was paid for according to a formula based on cost, a dispatch system with marginal cost pricing and a system of trading power between generators to meet customer contracts. Large-scale privatization began in 1986 and led to the (partial) vertical disintegration of the sector and the formation of a wholesale power trading mechanism. The Chilean reform was followed by the reorganization of the British electricity sector in 1990. The wholesale market only included England and Wales until 2005. In Australia, the market in Victoria and New South Wales began operating in 1994; followed by opening of Australian National Electricity market in 1998. The Nordic Market opened in 1992, initially in Norway, and later in Sweden, Finland, and Denmark. In North America, a number of north-eastern markets also began operating in the late 1990s, and so on."

Developed countries, such as the United States and European countries, applied management systems and administrative instruments to their free electricity market, which included as the creation of an electricity pool and establishing financial contracts to hedge against the risk of price volatility (Muñoz et al.,2013; Corchero, 2010). It seems that these developed management systems led to improved markets in these countries, making them benchmarks for other electricity markets to follow. Others countries used this knowledge in order to lay the suitable groundwork and establish strategies in order to improve their own electricity markets (Muñoz et al.,2013; Corchero,2010; Kotler and Armstrong, 2013; Weron, 2007).

One of these benchmarks can be considered the Spanish electricity market, which had enacted Law 54/1997 on the electric sector in November 1997, which strengthened its market as of January 1998 (Weron, 2007; Corchero, 2010; Muñoz et al.,2013). This tenets of the law established guarantees to the supply chain and the quality of electricity, as well as assurances to process power at a lower cost and having a nearly completed competitive market. Prior to 2007, Spain's electricity market was more centralized. It was also managed by three entities: the market operator (MO), the independent system operator (ISO) and the Red Electrica de España (REE). The law states that these entities are to set short-term market mechanisms, ensure a quality supply and maintain the high-voltage transmission network. "In this situation, the coordination between the MO and the ISO became essential in order to guarantee that the market transactions are physically feasible and fulfill the security criteria" In addition, they also were in cooperation with the OM and ISO on physical transactions and the fulfillment security (Muñoz et al., 2013;Corchero, 2010).

The Spanish MO was renamed the "Operador del Mercado Iberico de Energia - Polo Español" or OMIP in 2010, while the OMEL was responsible for managing the spot markets. Since the market was started in 1998, investments in power generation have led to the evolution of the market from a model with two power generation companies with 80% market quota to a framework where the highest quota among sector participants is 22% (see Muñoz,Heredia and Corchero, 2013 ; Corchero,2010).

At the current time, the market's pricing mechanism is based on a Day-Ahead market (DAM). DAMs allow agents to execute bilateral contracts. This system also permits the integration of open long-term positions with physical settlement in the market (Muñoz et al., 2013;Corchero, 2010). Recently, there have been some changes in the structure and ownership within the Spanish market, such as new entrants (Weron, 2007). After establishing the Iberian electricity market (MIBEL) in 2007, certain rules were announced in the energy production market regarding the day-ahead market, and the intraday market was also introduced. The new stipulations further encouraged a competitive production market. It also fostered the integration of the Spanish and Portuguese electricity systems, therefore making it convenient to improve earlier mechanisms in the Spanish electricity market (Muñoz et al., 2013; Corchero, 2010; Weron 2007; OMIP, 2015). More recently, the advent of renewable electricity in Spain raised the stature of the Spanish market as a developed model (Ciarreta et al., 2014). In other words, "The derivatives market and entry of other new market mechanisms resulted in the Spanish electricity market becoming more liberalized and de-centralized. One of these mechanisms is called 'Operador do Mercado Iberico de Energia - Polo Portugues', founded in 2008" (Corchero, 2010; Muñoz et al., 2013). In the long term, this electricity market aims to take part in and cooperate with other agents such as financial mediators, commercialization agents, producers, etc (Corchero, 2010; Weron, 2007). At the end of 2009, the number of sector participants in the market was 1169; 918 producers (621 special regime producers: renewable energies, waste and cogeneration), 192 distributors or suppliers and 59 other kinds of agents. The total installed capacity of the system as of December 2009 was 93729 MW".

However, the Spanish MO regards "the bids accepted by Generators Companies (Gen.Cos) on the spot markets" and investigates if these agents can participate in the derivative market. They are also examined as to whether they can adhere to the ancillary services market or adjustment market services. If they can, this means they have sufficient reliability and security guarantees to maintain system capacity (Corchero,2010; Muñoz et al., 2013).

Based on this section, the new mechanisms in the Spanish electricity market (MIBEL) are divided into two Bilateral Contract markets (BCs). BCs are based on two kinds of bids; one of them being CESUR (see OMEL, 2014), to maintain the liquidity of long (or medium) term markets. This mechanism is useful for supplying electricity at regulated prices and stabilizing the cost of energy for end consumers by preventing the volatility of the DAM prices (Muñoz et al., 2013; Corchero,2010). In this mechanism, a Gen.Co has to submit an accepting-price purchase bid to the DAM for the duration of the contract; however, this leaves no room for change or optimization.

The second BC market involves virtual power plant bidding or VPP, and these stimulate liquidity in a competitive market. This mechanism is based on selling electricity capacity virtually instead of through physical divestments by one or more dominant firms. Most BCs are settled before the DAM is formed, because VPP markets are formed afterwards. These mechanisms are formed for different reasons, perhaps due to certain restrictions on the electricity supply at peak load times, or to make the balance in MIBEL because this market must not be confused with other subsequent markets, such as ancillary services. But overall, BCs are often the result of classic bilateral trading between agents without the implications of a particular institution or other auctions in organized markets, such as the virtual capacity auction (mandatory for the dominant agents) or distribution auctions (Muñoz et al., 2013; Corchero, 2010).

As Muñoz, Heredia and Corchero (2013) explains, being responsible for the entire demand of the Spanish electricity market, these markets are integrated in the DAM and derivatives market. This is why the Intraday markets (IM) are formed just before and during the delivery day in these mechanisms. This way, all the agents cooperate and participate in the DAM, even agents using BC mechanisms. This strikes an important difference between the DAM and IM. The aim of the latter's market mechanisms is to manage and maintain energy transactions for the next day, see Figure 2.1.

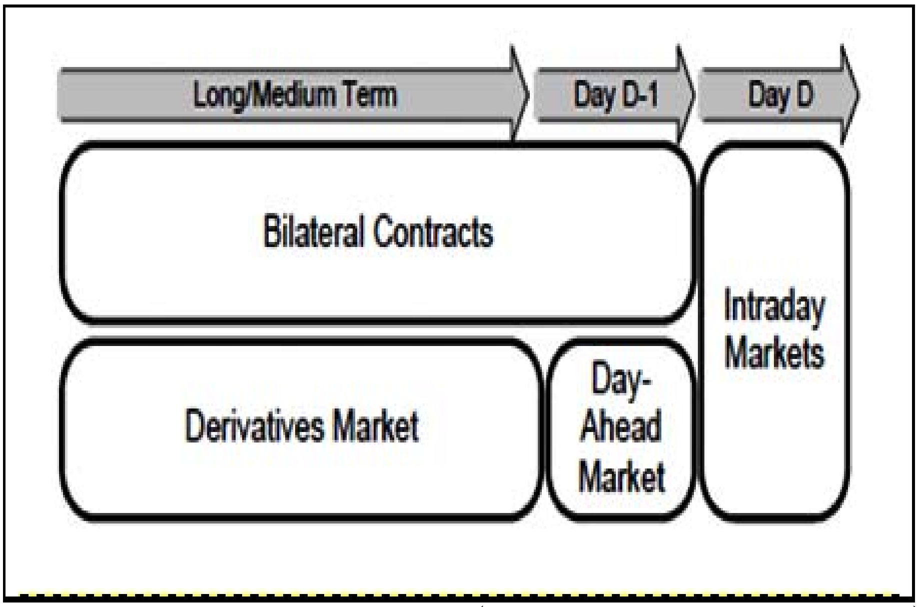


Figure 2.1: Spanish market mechanisms(Muñoz et al., 2013; Corchero, 2010;).

Furthermore, the spot price is attained via the sale and purchase offers of the market agents. These offers will be determined in the market during the 24 hours of the settlement day. Based on spot pricing mechanisms, the real time of the competition market is also established (Muñoz et al., 2013; Corchero, 2010).

In contrast to the Spanish electricity market, which is defined as a bilateral market, the Iranian electricity market is a not BCs market. In other words, in Spain the price is determined by the spot price, namely, the aggregated demand at a certain hour and the price elasticity of demand is not zero (Gonzalez and Basagoiti, 2000). It means that the spot price will be attained through bilateral contracts between two sides, the Spanish market suppliers and the demanders. But in the Iranian electricity market, there are some limitations to obtaining certain strategic information about the market price. This information, such as the marginal cost of most power plants, is unknown or unavailable in this market. In addition, although competitor bid curves are required for a considerable amount of time, this kind of data is not published or accessible anywhere in Iran (Asgari and Monsef, 2010).

Furthermore, the Market Operator has a strong role in determining electricity prices before the market is formed (amongst their beneficiaries) (Asgari and Monsef, 2010; Bigdeli and Afshar, 2009). In other words, companies to some extent have power over pricing, depending on their size, and access to information on the Iranian electricity market (Asgari and Monsef, 2010; Bigdeli and Afshar, 2009). Producers and consumers rely on price forecast information to prepare their corresponding bidding strategies (Asgari and Monsef, 2010).

Consequently, the mechanisms that have been developed provide a direction for this thesis to take in its comparison of the Iranian and Spanish electricity markets. It is clear that this research will help develop and implement some statistical methods for making a more exact estimate on the future behavior of the Iranian electricity market. A statistical analysis modelling will be used to contrast the Iranian market and a competitive (Spanish) model. Towards this aim, the research surveys the behavior of the main factors (price and load) in both markets comparatively. The relationship between these factors can also determine the degree of competition in these markets (Walter, 2004; Nicholson and Snyder, 2011).

Uncovering more strategic knowledge about the Iranian electricity market has led the researcher to present a forecast for Iranian electricity prices and loads. This is useful to determining the behavior of price and load as important elements in this market. It is known, for example, that "electricity price forecasting will be helpful to market players, and in particular, power generating companies, which must be able to manage their facilities and the associated economic risk" (Benini, 2002; Bigdeli et al., 2009).

On the other hand, there also is the evaluation of the impact of other economic factors on the Iranian electricity market, despite the great importance of price and load in forecasting this particular market. But there are some beneficiaries—such as Gen.Cos.—which will also try to maximize their own profits in this market according to other participants and other market factors (Bigdeli et al., 2009). For more detailed information about the importance of other economic factors in the energy market refer to Section 2.4 below.

2.4 Macro and micro economic factors in the Iranian electricity market

Most market studies related to the Iranian electricity market do not consider other economic factors which may have an impact on electricity prices (Aggarwal et al., 2009; Le and Vinh, 2011). Consequently, it is critical for market managers to take other elements—such as load—in account to modify their pricing strategies in the competitive market (Bunn, 2004; Kotler and Armstrong, 2013; Nicholson and Snyder, 2011; Weron, 2007).

Basic economic theories explain that price patterns against demand is predictable in competitive markets (Nicholson and Snyder, 2011). However, the probability of establishing any relation between load and price may be diminished when examining the Iranian electricity market; this may be due to the aforementioned restrictions on Iran's market structures. Therefore, this research suggests investigating the existence of the relationship between price and these market factors using a time series approach.

The advantages of having a competitive market have allowed since the late 1980s that policy makers and regulators in a number of countries have liberalized, restructured or "deregulated" their electric power sector. Typically, they introduced competition on the power generation and retail levels. These experiments have had vastly different outcomes, such as the rise of decision-making and support models in energy market management (Finn, 2000; Sioshansi, 2008; Ventosa et al., 2005). As a result, Iranian governmental bodies attempted to change the fundamentals of their electricity market, such as migrating the distribution sector from monopolization to privatization (Khalili and Mehri, 2007).

As a rule, the rate of market growth and restructuration can usually be affected by variations in economic factors (Aggarwal et al., 2009; Le and Vinh, 2011). Market managers must be able to consider other factors in order to make adjustments to market strategies, such as pricing approaches, to stay competitive (Bunn, 2004; Kotler and Armstrong, 2013; Nicholson and Snyder, 2011; Weron, 2007).

The research of Chris Harris into electricity market policies resulted in an accurate depiction of how prices are steered (Harris, 2011). He found that changes in markets and their prices are usually replicated in variations in economic indices and factors. For example, the volatility of electricity prices is determined by demand elasticity and variations, fuel prices, currency exchange rates, the availability of generating units, etc (Benini, et al., 2002).

In electricity markets, demand, the availability of different sources of power generation, fuel costs, etc. have an impact on prices and their behavior (USA Energy Administration, 2014a; Le and Vinh, 2011). On the other hand, a country's inflation rate (Aggarwal et al., 2009; Le and Vinh, 2011), exchange rate (Yu and Mallory, 2013; Sameti et al., 2004; Kilian, 2008; Adaramola, 2011) and energy prices such as the price of gas or oil (Boqiang and Dunguo, 2008; Farzanegan and Markwardt, 2009; Moutinho et al., 2011) also play a significant role in the energy market and economic activities (Le and Vinh, 2011; Kilian, 2008).

Taylor (2001) demonstrated “the role of exchange rates in monetary policies”. Adao et al.(2009) evaluated the relevance of the exchange rate regime for monetary policy stabilization. Yu and Mallory (2013) proved the “effect of the exchange rate that has on carbon credit prices in energy markets”. “The role of the stock exchange in corporate governance” was previously examined by Christiansen and Koldertsova (2008), while Simanovsky (2009) described “how the stock exchange works in capital markets”. Bahmani-Oskooee (1995), by using annual data from 1959-1990, determined that the severe rate of inflation after the 1978-79 revolution was due to the forming of the black market and the performance of the exchange rate. Jensen and Tarr (2003)in their study into Iran’s international economic activities, indicate that the country had to relinquish non-tariff barriers, the dual exchange rate system, and highly subsidized prices on petroleum products, as well as the use of market mechanisms as a means of regulating foreign trade, due to its commitments to the World Trade Organization (WTO)(Jensen & Tarr 2003)(Jensen & Tarr 2003)(Jensen & Tarr 2003)(Jensen & Tarr 2003)(Jensen & Tarr 2003)(Jensen & Tarr 2003).

Still, the price of energy tends to characterize the economy of a country. Asafu-Adjaye (2000) examined the relationship between energy prices and economic growth using a time series approach, applying it to some Asian developing countries such as India, Indonesia, the Philippines and Thailand. Moutinho et al.(2011) proved that natural gas price has an impact on Spanish electricity market prices. Boqiang and Dunguo (2008) assessed the roles of energy, oil and coal prices on the Chinese economy. Kilian (2008) explored the economic effects of energy price shocks in the U.S., while Finn (2000) examined “perfect competition” and the effects of increased energy prices on economic activity. Finally, Emery and Liu (2002) analyzed the relationship between electricity and natural-gas futures, proving, their co-integrated relationship.

On the other hand, Fischer and Merton (1984) explained the impacts of the stock market on macroeconomics, which they presented as “a good predictor of business cycles and components of the GNP”. “The term ‘stock market’ can be used to denote individual stock exchanges in various places or one market comprising all individual stock exchanges in country” (Bhole, 2004). Hence, Cong et al. (2008) have described the stock exchange price as one indicator of the stock market. They went on to investigate the interactive relationships between oil price shocks and the Chinese stock market. They also represented these evaluations using multivariate vector auto-regression.

These kinds of studies reinforce the idea of how economic factors and indicators affect energy markets. Further research has determined the types of relationships existing between electricity load or demand and electricity prices in the Iranian electricity market, with an analysis towards the importance of some of these indicators in the Iranian electricity market.

Some minor studies have taken into consideration the importance of factors such as the foreign exchange rate, stock exchange and natural gas prices and oil price in the Iranian electricity market. Because of the outsized role, these play in economic markets (Aggarwal et al., 2009; Le and Vinh, 2011; Finn, 2000), the effects of such factors on the behavior of Iranian electricity prices will be assessed in this thesis as one of the most important elements in this market.

This study will employ time series analysis to evaluate how these three economic factors are associated, which are examined two by two. Then, there will be an attempt to establish whether any linear relationship exists between them, as independent variables, and Iranian electricity prices, as the dependent variable. These discoveries will help distinguish the importance of other micro or macroeconomic factors and indicators in this market. The following sections will provide further explanation about the main role of USD/IRR exchange rate, the Tehran stock exchange, the oil and gas market spot price on the Iranian economy in particular by reviewing several other studies.

2.4.1 US dollars /Iranian Rails Exchange rate

The European Central Bank explains that foreign exchange rates play an essential role in globalized economies, having a strong influence over the flow of trade and pricing strategies in international markets (Filippo et al., 2008). This has been noted as far back as 1978, when Hooper and Kohlhagen proved the effect of exchange rate uncertainty on the international trade price between two countries, the United States and Germany (Amano and van Norden, 1998). Rose (1991) explained that "the exchange rate significantly affects the balance of trade" as related to the aggregate real trade balance in five major OECD countries.

Indeed, an exchange rate describes the price in terms of one currency at which another currency, or claims on it, can be bought and sold. The rate is expressed as the amount of one currency that is necessary to purchase one unit of another currency (Masoom, 2013). Exchange rates are described in different ways, such as the Spot Exchange Rate, Forward Exchange Rate, Bilateral Exchange Rate, Effective Exchange Rate Index, or the Real Exchange Rate (Riley, 2012).

The primary role of exchange rates on an economy is made clear in a vast study related to macroeconomic indicators. Isard (1995), in his book about the exchange rate in economy and its behavior, remarks about the index's impact on policy markets, international monetary regimes and the institutional characteristics of foreign exchange markets.

According to numerous economics studies, the exchange rate is highly important to the management of economic factors (such as inflation, monetary policy and etc) (Sundararajan et al., 1999; Korap, 2007; Shambaugh, 2004). To be specific, fluctuations in the exchange rate exert influence on both export and import commodities markets, as well as the interest rates in money markets (Shambaugh, 2004). Kisinbay et al. (2009) pointed to the exchange rate as one of the most important monetary policy tools for emerging economies. Interestingly, Amano and van Norden (1998) noted a tight relationship between the real domestic price of oil and the real effective exchange rate, particularly in Germany, Japan and the United States. It is widely known that the US dollar is the most important reserve currency in the world and most of international commercial transactions are made in dollars (Pernet et al., 2012).

In order to demonstrate the weight of the exchange rate on the energy market, Sadorsky (2000) investigated the connection between the two. This relationship was also explored by Muñoz and Dickey (2009), who pointed to the importance of the foreign exchange rate, in this case as to Spanish electricity prices

Furthermore, other types of exchange rate systems also make an impact on a country's economy, such as floating exchange rates, pegged floating, crawling pegs, fixed rates, currency boards and dollarization (Mussa et al., 2000). An exchange rate regime, for example, is defined as the set of rules that governs the foreign exchange rate market and their subsequent prices (Beckerman, 2005). Such a regime or system does account for inflation performance, although it is difficult to infer its effect on growth. Nevertheless, policy variables, etc. having an influence on economic activity tend to have different effects on growth under different exchange-rate arrangements (Domaç et al., 2001). It was Giovanni and Shambaugh (2008) who examined the relationship between the annual growth of the real GDP and interest rates in various exchange rate regimes in different countries. Consequently, they found each kind of system, such as fixed exchange rates and countries with a pegged system, yields different results.

From the 1970s until the March 2002 unification, the exchange rate system of the Islamic Republic of Iran was highly controlled, featuring multiple exchange rate practices with their associated exchange restrictions and import controls. The "official exchange rate refers to the exchange rate determined by the national authorities or the rate determined in the legally sanctioned exchange market. So, it is calculated as an annual average based on monthly averages, the local currency units relative to the US dollar" (World Bank, 2014). The two remaining official exchange rates for the Iranian Rials (IRR) were unified in March 2002" (Celasun, 2003).

In these years, there were great repercussions due to the impact of the eight-year war with Iraq, the collapse of oil prices, trade sanctions that create a shortage of foreign currency, and the rise of black market premiums (Pesaran, 1992; Valadkhani and Nameni, 2011). This led to "the formulation of the demand for money by Iran" (Bahmani-Oskooee, 1997). At that point, the authorities adopted the rate of Iranian Rials per US dollar in order to decrease the exchange rate gap effecting economic growth (Abounoori and Zobeiri, 2010; Celasun, 2003). "On March 21, 2002, a unified exchange rate regime, based on a managed floating exchange rate system and the former official exchange rate of 1,750 Rials per US dollar was abolished" (Fund, 2004).

Despite the regulatory changes made to Islamic Republic's exchange rate system, the Iranian Central Bank reports the USD/IRR exchange rate to be reference rates, in consideration of the multiple-tier exchange rate regime which was in place in the prior system. (refer to International Economics, 2000).

However, "prior to March 21, 2002, the foreign exchange market operated mostly a multiple exchange system, consisting of two officially approved rates:

(a) an official exchange rate pegged at 1,750 rial per US dollar, which applied mainly to imports of essential goods and services as well as servicing public and publicly guaranteed debt; and (b) an effective Tehran stock exchange rate (TSE), applicable for imports from a positive list issued by the ministry of commerce" (Fund, 2004).

Nowadays, the USD/IRR spot exchange reference rate (IDEX) is applied to the currency at today's market prices (Riley, 2012), which is represented by Islamic Republic of Iran (International Economics, 2000).

Overall, these studies indicate a need to investigate the importance of the USD/IRR exchange rate on Iranian electricity market prices. This will help to shed light on exactly how the rate fluctuations influence price behavior. This thesis will examine whether or not any relationship exists between the Iranian electricity price and the foreign exchange rate.

2.4.2 Tehran Stock exchange

Stock exchanges are now considered one of the most important financial institutions in today's economy. "A stock exchange is a market where securities are bought and sold; securities are certificates conferring ownership in a certain property or company" (Hafer and Hein, 2007). All kinds of securities, bonds, warrants, and options can be issued, including stocks, foreign currency and etc.

Understanding how the stock exchange works is absolutely essential when making investments. In fact, today a large sector of the population is directly or indirectly involved in the capital market. When a company is founded, it can issue or distribute stocks in the stock market. The founders can decide what section of the company each of them will own (Simanovsky, 2009).

"The term stock market can be used to denote an individual stock exchange in various places or one market comprising all the individual stock exchanges in a country" (Bhole, 2004). Trading in securities dates back over 200 years. The London Stock Exchange and the United States Stock Exchange began around 1700 (Michie, 2001; Simanovsky, 2009), Spain's securities markets began trading in 1836 (Investopedia, 2014). The Tehran Stock Exchange (TSE) is a major stock market in Iran, which began its operations in 1967 (Tehran Stock Exchange, 2014).

Due to the role stock markets play in their countries' economy, their impact on the systems of financial development and economic growth (Arestis et al., 2001) must be considered within a developed market, or even a liberalized one (Henry, 2000).
Consequently, many companies around the world hope to earn a place on the list of their respective stock markets. In Iran, there were only six companies in the first year of Tehran stock exchange. Nowadays "the TSE has evolved into an exciting and growing marketplace where individual and institutional investors trade the securities of over 420 companies" (Tehran Stock Exchange, 2014; Lakshmanan and Nijkamp, 1980).

"The progression of the TSE can be divided into three periods: from the time when the TSE was begun until the revolution (1967-1978), from the revolution until the end of the imposed war (1979-1988), and from the end of the imposed war (1989-2006)" (Tehran Stock Exchange, 2014). In 2006, the TSE was demutualized, which refers to the process by which an exchange becomes a publicly listed entity, as it had been privately owned by the brokers affiliated to exchange (Bacha and Mirakhor, 2013).

Iran's financial system, the largest Islamic financial system in the world, has undergone major transformations "Iran's capital markets (the TSE, the OTC market, the commodities exchange) have gained importance in the government's strategy of promoting a more market-oriented economy and mobilizing private capital (in the financing of the economy)" (International Monetary Fund, 2011) .

The Council of Ministers approved "regulations governing foreign investment in the exchange and OTC markets" on April 18, 2010 (Tehran stock exchange, 2013). The TEPIX, the weighted market value of the all share prices appearing on TSE price board is considered the main index in the Tehran Stock Market (Henry, 2000).

The volatility of the TEPIX may reflect a certain economic ambiguity (Athari, 2011). The Iranian parliament, to support investors' rights and with the aim of organizing, preserving and developing a transparent, fair and effective market, passed the Securities Act on November 16, 2005. The market's Members' Council is governed by ministry officials and the Central Bank of Iran (Tehran Stock Exchange, 2014).

Well-developed stock markets in most countries also feature established banks and non-bank financial intermediaries (Arestis et al., 2001). "Monetary policy developments are also associated with security return patterns" (Panettal, 2002). Gjerde and Saettem (1999) have demonstrated the influence of the stock market by investigating "causal relations amongst stock returns and macroeconomic variables in a small, open economy".

All these different studies involving stock markets—as a capital market—lead to the need to research their effect on the electricity market. Without a comparison of other activities, however, an analysis of its impact may not be meaningful (Kotler, 2010). As indicated above, the Tehran stock market is known as the largest and most important stock market in the Islamic Republic of Iran, therefore, the Tehran stock exchange price index (TEPIX) has been chosen in order to investigate its relationship with Iranian electricity prices.

2.4.3 Oil price and gas price

Nowadays, it is well-accepted to consider the importance of energy prices in every sector of the economy. There are a large number of studies that discuss the effects of energy prices on the performance of national macroeconomic indicators, such as inflation (Bohi, 1989; Hope and Singh, 1995), growth (Asafu-Adjaye, 2000), the GDP (Baclajanschi et al., 2006) and monetary policy (Brown and Yücel, 2002):

- Hamilton (1983) found a high correlation between oil price fluctuations and the growth of the U.S. GNP, while Guo and Kliesen (2005)later determined that a volatile oil price has a significantly negative effect on the future growth of the gross domestic product or GDP.

- Hamilton (1996) demonstrated the historical correlation of oil prices and recession in the US, as well as investigating, this time in 2011, the macroeconomic effects of oil prices through a nonlinear approach in a literature review (Hamilton, 2011).
- Cunado and de Gracia (2005) explained there is a short-run, Granger causality relationship between oil prices and economic growth rates.
- Lee and Ni (2002) evaluated the effects of oil price shocks on demand and supply in various industries and determined both demand and supply are affected by oil price shocks.
- Erygit (1969) pointed to the dynamic relationship amongst oil price shocks and interest rates (Lescaroux and Mignon, 2008).
- Lescaroux and Mignon (2008) also represented the influence of oil prices on economic activity and other macroeconomic and financial variables using Granger-causality tests, the evaluation of cross correlations, and co-integration analysis, among other methods.
- Farzanegan and Markwardt (2009) investigated the dynamic relationship between oil price shocks and major macroeconomic variables in Iran by applying a VAR approach; they demonstrated both positive and negative oil price shocks significantly increase inflation.
- Papapetrou (2001) used a multivariate vector-auto regression approach in order to research the dynamic relationship among crude oil prices, real stock prices, interest rates, real economic activity and employment in Greece (Hamilton 2011).

On the other hand, world oil prices have a serious effect on a country's economy. In 1975, nine international economists described that the quadrupling of oil prices in developed countries (such as the United States and Japan in 1973-1974) caused an economic recession in non-oil producing countries (Fried et al., 1975). Lutz and Meyer, (2009) investigated the impact of both higher oil and gas prices on German international trade, as well as describing the role of gas prices on the economy.

In competitive markets, this depends on how pricing is done in regards to natural gas decontrol, consumption and salaries; this could change the industrial production, earnings, etc (Purdue University. 1983).

Shahidehpour et al. (2005) proved the impact of natural gas infrastructure on electric power systems. Kliesen (2006) stated that natural gas was the most important energy source in the U.S. economy. Based on the Tavanir Company's statistical report on 44 years of activity in Iran Electricity, the most part of fuel consumption at power plants, which generate electricity using thermal power generators, belong to natural gas and the oil in this market (Tavanir, 2011c).

OPEC (the Organization of the Petroleum Exporting Countries), in addition to its mission "to coordinate and unify the petroleum policies of its member countries and ensure the stabilization of oil markets", "it also collects and analyzes a vast amount of industry-related data", such as crude oil price per basket (OPEC website , 2014). In

2004 Dees and others explained the role of this organization on real oil prices in world markets. They also reported its influence on the "Organization of Economic Cooperation and Development (OECD)" (Kaufmann et al., 2004; OECD, 2014). Iran, of course, is also one of the main members of the OPEC, which was founded in September 1960.

On the other hand, the International Energy Agency (IEA) was founded in order to respond to major disruptions in the oil supply by the release of emergency oil stocks into the global market (IEA 2014). Iran is not a member of the IEA, although it does have ties to the agency because of the increasingly global energy market. Some IEA members are from the OECD, such as the United States, Spain and so on (US Energy Information Administration (EIA), 2014; OECD, 2014). In general, the OECD consists of the United States, much of Europe, and other advanced countries. These countries total 53 percent of the world's oil consumption (EIA, 2014).

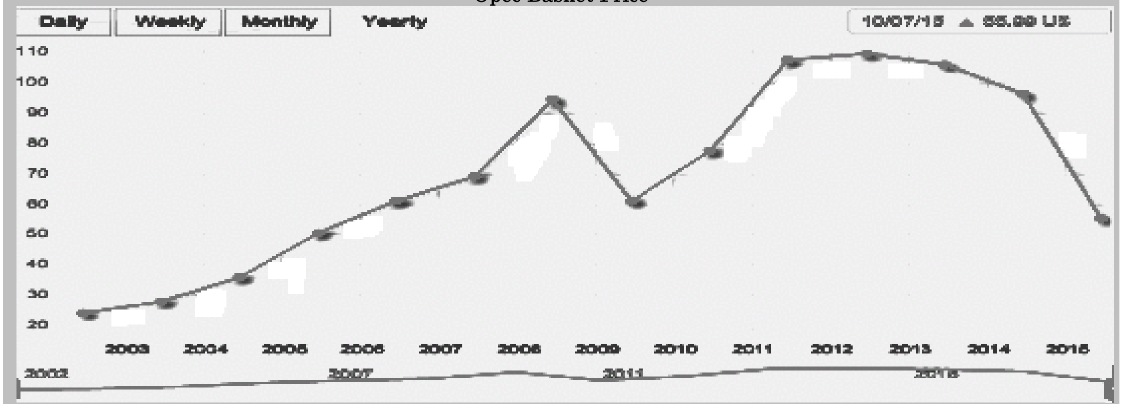
The review of these studies proves the highly important role played by energy price fluctuations on macroeconomic variables. In particular, the price of crude oil and natural gas has significant influence on international energy markets. In addition to the OPEC basket price, two other crude oil price indexes are used. The "Cushing, OK WTI Spot Price FOB (Dollars per Barrel)", utilized by the United States as one of the top oil producers and member of the IEA, and also the "European Brent Spot Oil Price FOB (Dollars per Barrel)" (EIA, 2014) (see Figure 2.2).

In general, it would seem that the all three price indexes perform in similar ways, despite slight differences between them (see Figure 2.3). What is more, these time series are run daily and displayed on the OPEC and U.S Energy Information Administration websites (EIA, 2014, OPEC website, 2014).

"Brent represented solely the North-West European sweet crude market, but since it has been used as the benchmark for all West African and Mediterranean crude, and now for some Southeast Asian crudes. It is also directly linked to a larger market" (EIA, 2014; Energy and Capital, 2014). Therefore, this thesis has taken into account these economic factors to further its aim of acquiring strategic knowledge of the Iranian electricity market by surveying the impact of these factors on Iranian electricity prices, known to be the main element in the energy market.

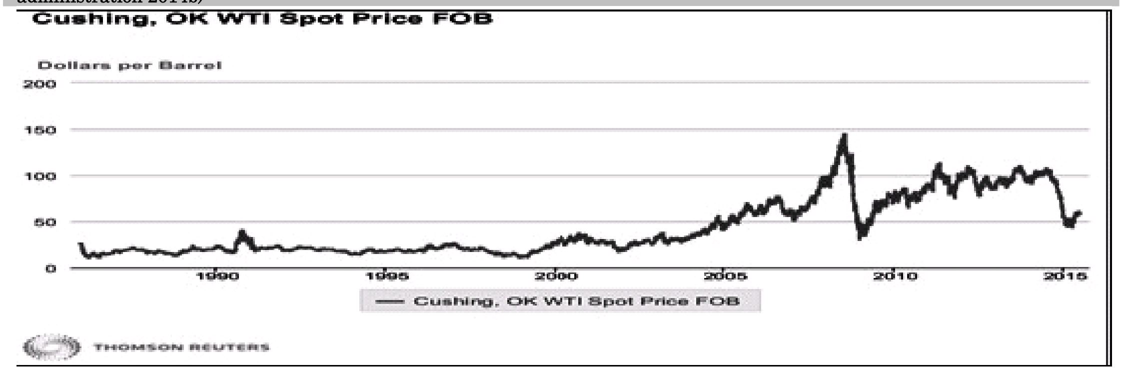
In a similar study in Turkey, Soytas et al.(2009) evaluated the significance of world oil prices on macroeconomics variables and its metals market. Similarly, this research surveys the relationship between the Europe Brent Spot Oil Price FOB (Dollars per Barrel) and Iranian electricity.

Opec Basket Price



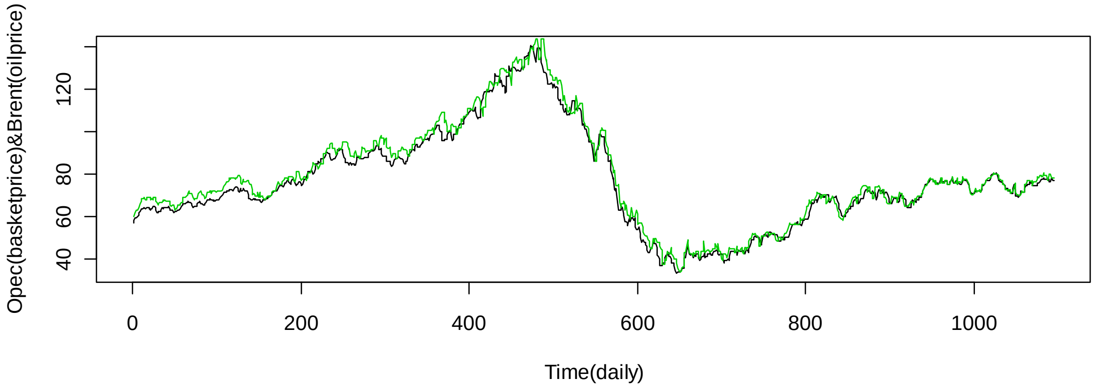
The new OPEC Reference Basket (ORB): introduced on 16 June 2005, is currently made up of the following: Saharan Blend (Algeria), Girassol (Angola), Oriente (Ecuador), Iran Heavy (Islamic Republic of Iran), Basra Light (Iraq), Kuwait Export (Kuwait), Es Sider (Libya), Bonny Light (Nigeria), Qatar Marine (Qatar), Arab Light (Saudi Arabia), Murban (UAE) and Merey (Venezuela). Notes:
As of January 2006: The Weekly, Monthly, and Quarterly and yearly averages are based on daily quotations.
As of January 2007: The basket price includes the Angolan crude "Girassol".
As of 19 October 2007: The basket price includes the Ecuadorean crude "Oriente".
As of January 2009: The basket price excludes the Indonesian crude "Minas".
As of January 2009: The Venezuelan crude "BCF-17" was replaced by the crude "Merey".

1-Crude Oil “A mixture of hydrocarbons that exists in liquid phase in natural underground reservoirs and remains liquid at atmospheric pressure after passing through surface separating facilities”
WTI - Cushing ;West Texas Intermediate
2-Barrel A unit of volume equal to 42 U.S. gallons
3-FOB (or free on board) is related to “a transaction whereby the seller makes the product available within an agreed on period at a given port at a given price; it is the responsibility of the buyer to arrange for the transportation and insurance”(USA energy administration 2014b)

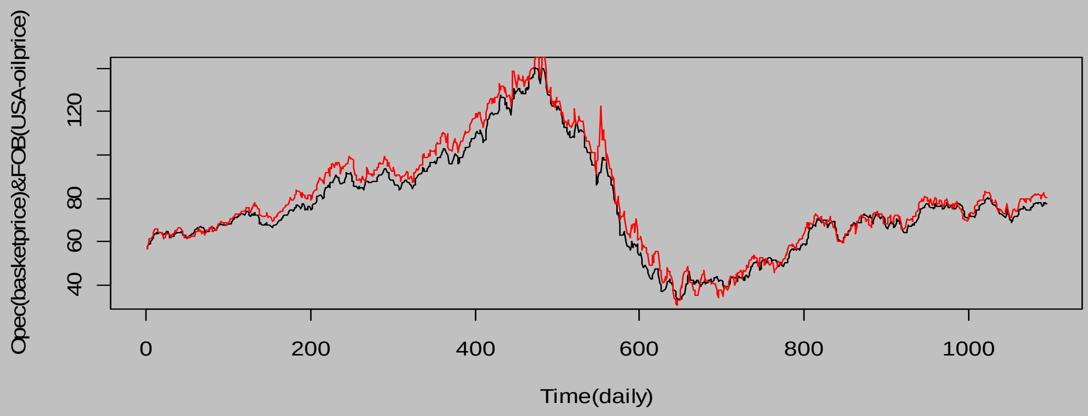


Brent: A crude stream produced in Texas and southern Oklahoma which serves as a reference or "marker" for pricing a number of other crude streams and which is traded in the domestic spot market at Cushing, Oklahoma.

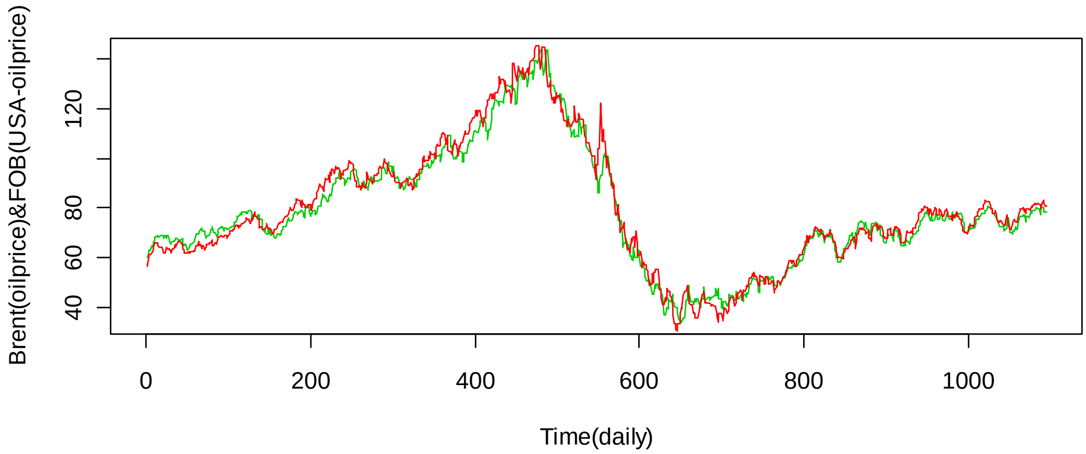
Figure 2.2: Energy price (OPEC and FOB);
Section one- OPEC Basket price (OPEC website , 2014). Section two- Cushing, OK WTI Spot Price FOB. Section three- Cushing, OK WTI Spot Price FOB (third graph) (EIA, 2014)



Black line: OPEC Basket Price. Green line: Brent Spot Oil Price



Black line: OPEC Basket Price. Red line: US oil price



Green line: Brent Oil Price. Red line: US oil price

Figure 2.3: Three overlapping time series of daily energy prices; OPEC Basket Price, Europe Brent Oil Spot Price and WTI Spot Price FOB (US oil price) –(2007-2010).

On the other hand, the United States has long had an important role in the global economy (Dées and Saint-Guilhem, 2011). The Henry Hub underground deposit was built in May 1988 and is the largest such hub in the United States (World Bank Publications, 1999), known as the official delivery mechanism for the world's first natural gas futures contract (Energy Equity Group, 2014), with about 550 million cubic feet of gas a day are transported through this market and now, the Henry Hub uses the average natural gas price of its 13 interconnected pipelines (Energy Equity Group, 2014). In other words, it is the most important natural gas spot market (World Bank Publications, 1999) (see Figure 2.4).

As explained previously, because of the macroeconomic impacts of natural gas prices Caloghirou et al.(1996) and Emery & Liu (2002) presented an analysis of electricity and natural gas futures and demonstrated the co-integrated relationship between them. Based on the importance thereof, this thesis also examines the effect of natural gas prices (specifically, the Henry Hub Natural Gas Spot price) on prices in the Iranian electricity market.

Overall, by evaluating the connections and correlations between these economic indices and the Iranian electricity price, more strategic knowledge about this energy market will be determined. Undoubtedly, the evaluation of the influence of these kinds of factors on the Iranian electricity price will prove essential. An analysis of these economic factors in the Iranian electricity market helps discover what kinds of factors have an outsized role in this market. In the light of this research, certain statistical time series methodologies will be employed, which will be explained in detail in Chapter Four.

Figure 2.4: Natural gas spot price: Daily Henry Hub Natural Gas Spot Price (EIA 2014a).

2.5 Background of methodologies

The theory and application of time series analysis have developed rapidly since its first appearance in 1970, thanks to the seminal work of Box and Jenkins (Box et al., 2013; Makridakis and Hibon, 1997). The main objectives of the time series analysis modelling are: data collection methods, such as hourly, daily, etc.; the dynamics of behavior patterns in the time series; the law of probability that governs observed time series; and using intervention for forecasting and controlling future events (see Box, Jenkins and Reinsel (1994); Hu (2011); Jianqing and Qiwei (2005); West et al(1994)). On the other hand, time series analysis depends on having proper statistical models. Most of the time, the validity of parametric models for large amounts of real data justified over a long period of time is considered questionable (Chan et al. 2004). The original idea of proposing theory and applying time series analyses was formed by Box and Jenkins in 1970, for more detailed information see Box,Jenkins and Reinsel (1994); Brockwell and Davis (2006); West et al (1994); Hu (2011); Jianqing and Qiwei(2005). The two also generated the "autoregressive-moving-average" or ARMA. referring the reader to the following Armstrong (2001); Box and Jenkins and Reinsel (1994); Hu (2011); Makridakis and Hibon (1997); West et al.(1994); Wurtz et al.(2006) for more precise definitions. Most of the popular classes of linear time series models are useful in the stationary process (Chan et al. 2004). The "autoregressive integrated moving average" or ARIMA models are generally based on the ARMA model theory (Box and Jenkins, 1994; Brockwell and Davis, 2006). The ARIMA model can be considered as a particular type of mathematical regression model (Chan et al. 2004).

This thesis provides a comparison between the Box-Jenkins' classic time series modeling approach and a nonlinear approach. Over the years, ARIMA forecasting models for economic variables became highly developed and estimated, to be subsequently applied for ex-post and ex-ante forecasts. Note that, with these regression models, only qualitative properties can be used (Jianqing and Qiwei, 2005). This means ARIMA models can be useful, due to their lack of knowledge of the function forms of the model, or local linear modelling. However, these models do not provide a good approximation of nonlinear phenomena.

The ARIMA model is a particular type of mathematical regression model, utilized to approximate the behavior of observations in scenarios where data exhibits a non-stationary movement (Armstrong, 2001; Box et al.,1994; Brockwell and Davis, 2006; Box, et al., 2008; Cryer and Chan, 2008; Makridakis and Hibon, 1997; Wang and Jain, 2003; Wurtz et al., 2006). Therefore, Hyndman and Fan (2010) applied the nonlinear model of "Density Forecasts" in order to provide an estimate of the full distributions of possible future demand values. In contrast to regression-form models, ARIMA models (also known as parameter-based models) are utilized to analyze the observations in complicated stochastic processes (Cryer and Chan, 2008; Wurtz et al., 2006).

In his book, Tsay explained non-parametric models (such as multivariate Kernel Functions) and conditional Heteroskedastic models, such as the GARCH model (see Tsay, 2005). These conditional heteroskedastic models are applicable to both nonparametric and parametric time series analysis models(Hu, 2011). In time series, conditional occurrences such as variance and mean have led the researcher to introduce "Generalized Autoregressive Conditional Heteroskedastic model". Studies considering a "conditional heteroskedastic model" are useful in improving other models (e.g., APARCH, and ARCH/GARCH models) and their related theorems (Bollerslev, 1986; Wurtz et al., 2006).

There are also other types of nonlinear models, including Parametric Nonlinear Time Series Models, such as the TAR or SETAR models (Narzo, 2008)). Tong (1978) was the first to present the TAR model and also developed the threshold at the practice, which meant carrying out exorbitant amounts of computer experimentation in order to present the SETAR (self-exciting threshold autoregressive) model (Hsu et al., 2010). The majority of Tong's work (1970) tackles nonlinear problems by breaking down the unknown function with linear approximation, each into a subset of the state space of the process. The partition is typically dictated by the so-called "threshold" variable. This type of specifications has been widely used to model nonlinear phenomena in different fields, such as biology, physics, economics and finance (Ulloa, 2005).

Tsay (1989) applied the threshold autoregressive models and presented a test for threshold nonlinearity, while Le Baron in 1992 introduced different levels of volatility as the regime-determining process (Chan et. al, 2004). Kräger and Kugler (1993) estimated "m" significant threshold effects on the exchange rate using the SETAR model. Most early studies of the SETAR model are based on stationary problems(Hyndman and Fan, 2010). However, the aforementioned studies improved the validation criteria for SETAR models, and three kinds of SETAR models have been developed. These SETAR models have been specified according to two and three regimes. It has been shown that their performance can be assessed against a simple linear AR and a GARCH model (Hyndman and Fan, 2010). Variations of these time series models are dependent on the time series context; the parametric time series models provide powerful tools for analyzing time series data, provided the model is correctly specified. In truth, the difference between parametric and nonparametric models is that the flexible non-parametric model reduces the modelling bias by describing the law, thus generating the data (Jianqing and Qiwei, 2005).

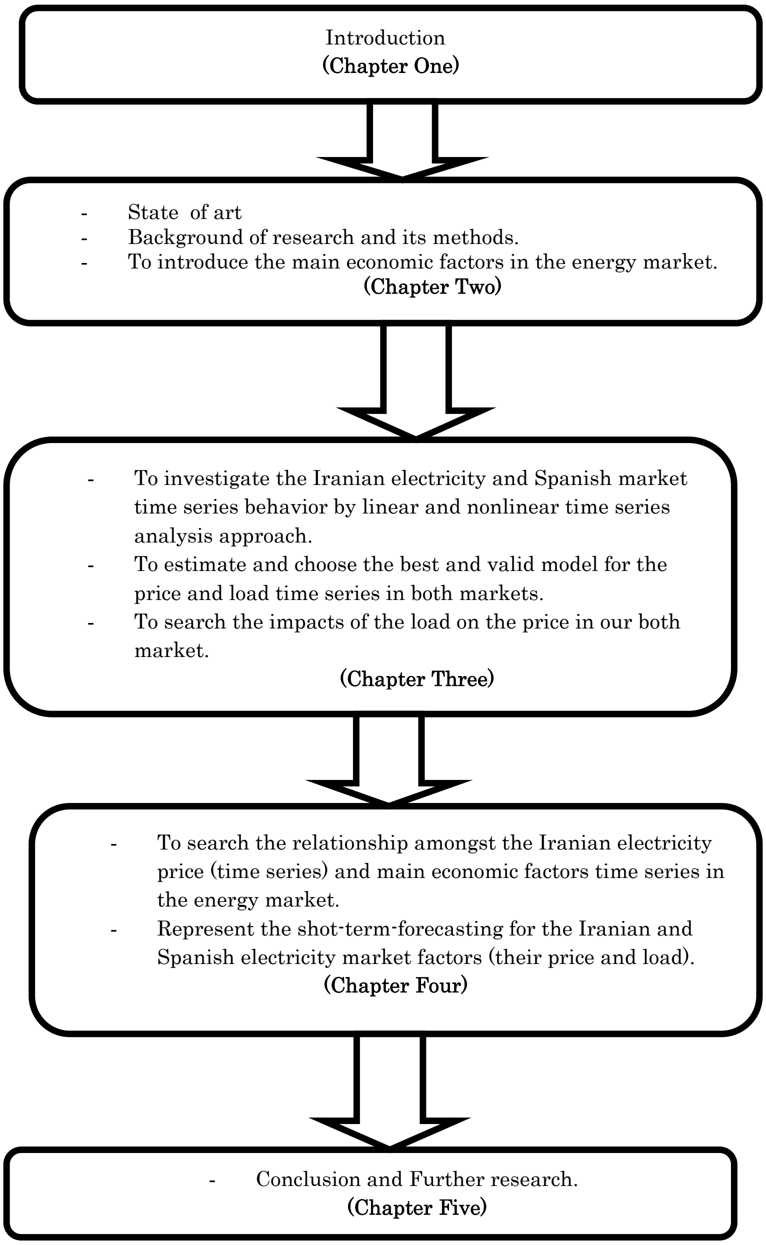
On the other hand, in order to obtain further knowledge of the Iranian electricity market, the research attempts to discover the type of correlation between macroeconomic and microeconomic indicators and the time series of Iranian electricity prices. "There are numerous statistical procedures that you can use to examine bivariate relationship" (Allen, 2004). These methods include Karl Pearson's correlation coefficient (Sharma, 2007), Kendall and Spearman's rank correlation coefficient (R Documentation(CRAN) 2014; Pillwein, 1970), and the Anova chi-square test (Allen, 2004), which include the association between two variables. These are different correlation calculation methods based on the nature of the variables (and their relationships) and various degrees of measurement, (refer to O'Rourke et al., 2005). One of the most often-used statistical quantities is Pearson's Correlation Coefficient; it measures the degree of (linear) interrelations between two sampled data.

According to these methods, the time series for Iranian electricity prices and the other previously mentioned economic indices are measured over time with the generic goal of yielding a correlation analysis of bivariate time series in order to evaluate the evidence of the influence of one time-dependent variable over the other (Yau, 2013).

The importance of this project is that it helps to provide more knowledge about the Iran electricity market through these kinds of modelling approaches and methods. This will eventually lead to greater efficiency. In addition, it provides more exact knowledge and a future estimation for the decision makers and managers of this market as to the liberalized and developed market.

2.6 Steps of the thesis

, kThe general organization of current study is as follows:



Chapter Three

3 Data description and time series modelling analysis

This chapter focuses on modelling the four time series: Iranian electricity prices (IEP), Iranian electricity load (IEL), Spanish electricity prices (SEP) and Spanish electricity load (SEL) employing approaches in time series analysis. Here, five sections will be justified. The first and second sections will relate data descriptions and propose certain estimate models for the daily Iranian electricity market. In other words, these concern daily time series for electricity prices and load. The third and fourth sections are devoted to the daily Spanish electricity market, also investigating the same two market indices—price and load—via time series approaches. In all four sections, different estimate models will be represented in time series for each index. Then, the most suitable model will be demonstrated for each time series according to the individual comparison of their results. The fifth and final section illustrates the role of load in the price of each electricity market.

3.1 Time series analysis of the Iranian electricity price

This section is divided into three parts: the first devoted to a data description of the Iranian electricity price (IEP), the second to its time series modelling, and the third part the results ascertained in this section.

3.1.1 Data description of the Iranian electricity price

Electricity sales were priced in various consumer sectors according to a constant rate in 2004 (CPI). According to the “statistical reports on 44 years of activity in the Iran Electric Power Industry (1967-2010)”, despite increased investment in the electric power industry during this period, a significant variation in the average price rate can still be recognized; see Figure 3.1 (Tavanir, 2011c).

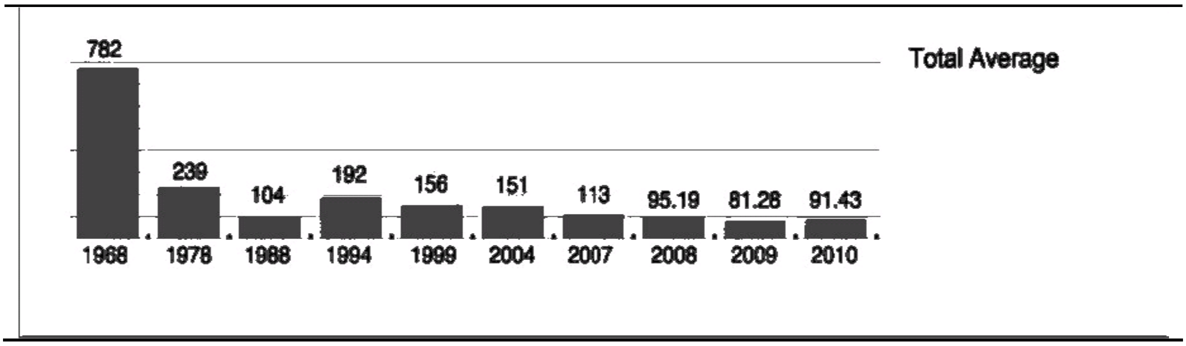


Figure 3.1: Total Average Rate of Iranian Electricity Sales to various consumer sectors based on the 2004 constant price (CPI) (Tavanir 2011c).

Natural gas also plays a crucial role in prioritizing the strategic plans of domestic electric power generation and regional export (Mirsaeedi, 2007); see Figure 3.2. In this graph, decimals are defined by the symbol '/' (Tavanir, 2008).

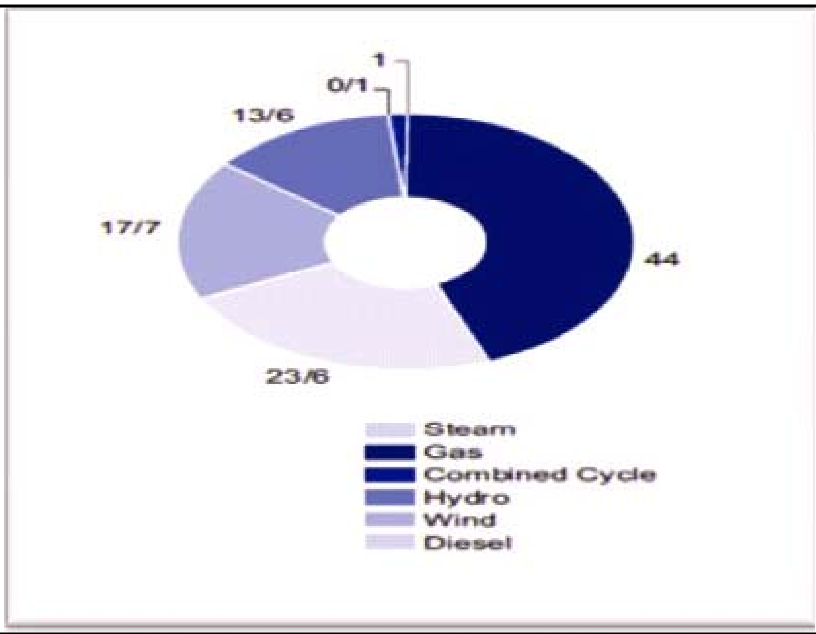


Figure 3.2: Percentage of various resources in Iranian power (electricity) generation (see Tavanir, 2011c).

In addition, the Tavanir company report identified that the electricity price covered the costs of three important sections of the electric power industry: generation, transmission and distribution (Tavanir, 2008). The point here is that 85% of the power generated was still being controlled and managed by the Ministry of Energy (Mirsaeedi, 2007). According to Figure 3.1 (Safakish and Manzur, 2009), electricity prices exhibited significant variations despite the fact that during this period, power generation always followed the demand rates (Tavanir, 2008).

The importance of electricity pricing and the variations in the market (Weron, 2007) caused this researcher to monitor Iran's daily electricity price time series over the course of three years in order to track the corresponding market response. The data was calculated daily, compiling the resulting data beginning on March 21, 2007 (corresponding to the beginning of the Iranian New Year of 1386) and ending on March 20, 2010 (the end of Iranian year 1388). The daily electricity price time series is calculated according to the "hourly accepted weighted average price (WAP)", an officially established quantity based on the Rials/kWh (Ministry of Energy of the Islamic Republic of Iran, 2010).

The prices were reported daily in order to have a suitable estimate model and thus a better investigation of market behavior. Consequently, the valid price demonstrates an indication of the overall performance during a 24-hour period. The total number of observations is 1095 for Iranian electricity price. The "R" programming software was used as the statistical analysis tool (R Development Core Team, 2011a). Previous observations suggested that it would not be necessary to employ a logarithmic transformation function due to the approximately constant variance (Muñoz and Dickey, 2009).

Figure 3.3 demonstrates an IEP time series during this period. This plot exhibits an upward trend in the daily values. Initially, it gradually increases, but then follows with a noticeable reduction. Finally, there are sudden spikes occurring on special dates. These variations clearly suggest that the IEP does not exhibit any linearity whatsoever. Some breakpoints in the time series have also been identified; two of these are shown via the red lines in Figure 3.3. The existence of these breakpoints will undoubtedly influence the choice of time series model, as they indicate the thresholds of the research observations (Tsay, 2005).

Considering the IEP time series plot, three distinct section motions can be pinpointed. These are as follows, as shown in Figure 3.3 and Figure 3.4:

a) March 21, 2007 to March 19, 2008 (one full year)
b) March 20, 2008 to November 25, 2008 (four months remaining in the Iranian calendar)
c) November 26, 2008 to March 20, 2010.

According to the statistics described in Table 3.1, the mean difference in the data is very significant. Moreover, the distribution of standard deviation is different in each sub time series. These three sections exhibit asymmetry since the skewness value is positive (or negative). Moreover, this indicates that the density probability functions in the time series have a tail on the right side (the left side for negative values) and the bulk of the distribution is concentrated on the right (left) in the time series distribution.

In addition, based on the p-values of the skewness test (with values under 0.05), a null hypothesis of skewness=0 is not accepted for each time series section. Moreover, as far as kurtosis is concerned (a null hypothesis where kurtosis=3), the p-value in the first section of this test is less than 0.05 (the predetermined significance level), which again suggests that a null hypothesis can be rejected here. However, in the second and the third sections, the kurtosis test results in a value greater than 0.05. Hence, the null hypothesis cannot be rejected. These results suggest that the three sections of the series exhibit asymmetry and there is a tail on the left side of the distribution. As in the first section the kurtosis is close to 0, indicating there is a heavy tail. Finally, for all sections, the p-value of the “Jarque-Bera Normality Test” is less than 0.05, proving that the skewness and kurtosis do not match a normal distribution (Bai and Ng, 2005).

The time series distribution is not unique either, which suggests there is “trimodality” existing in the data (Narzo, 2008). Also, the mean and median of the three sub-time series distributions are not equal in Table 3.1 (Muñoz and Dickey, 2009). The time series histogram shown in Figure 3.6 proves that the time series exhibits three separate distributions and bimodality of its data. Moreover, the “summary of descriptive statistics” indicates a significant difference between the minimum and maximum prices related to each sub-time series.

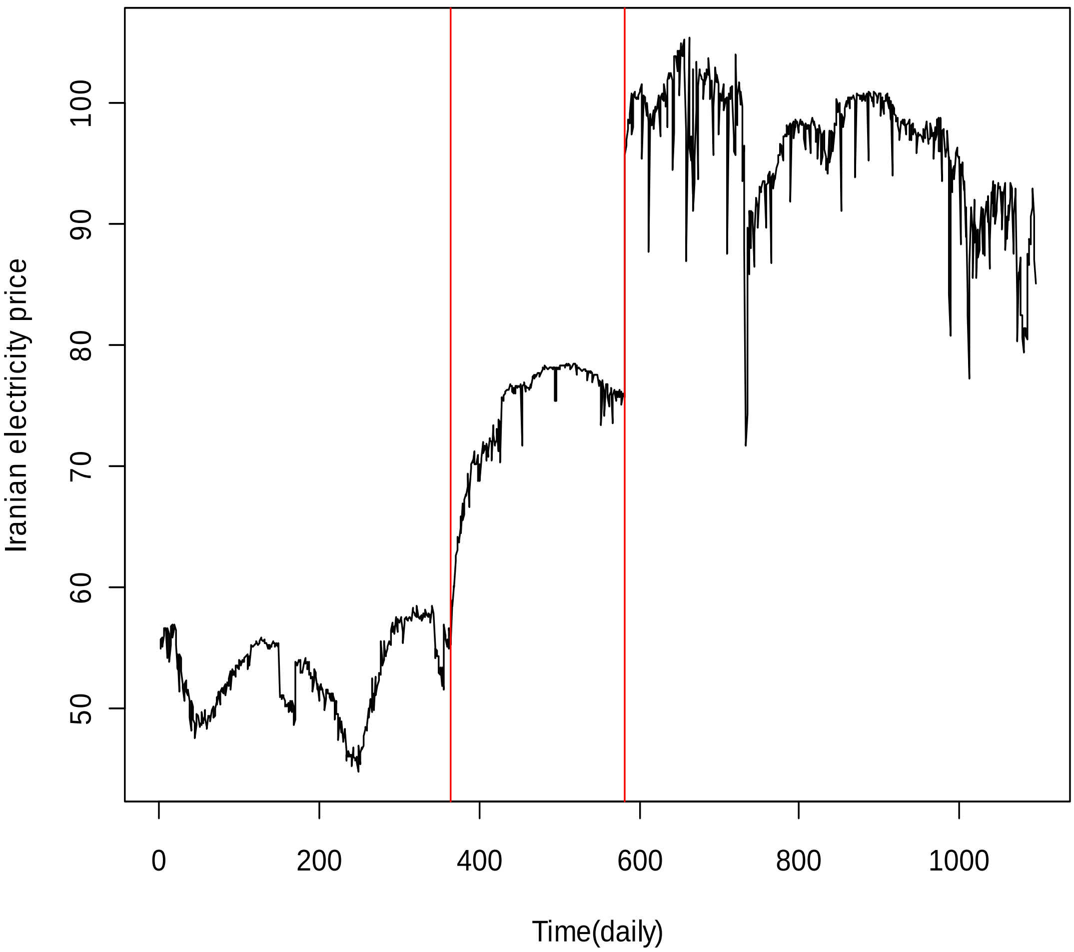
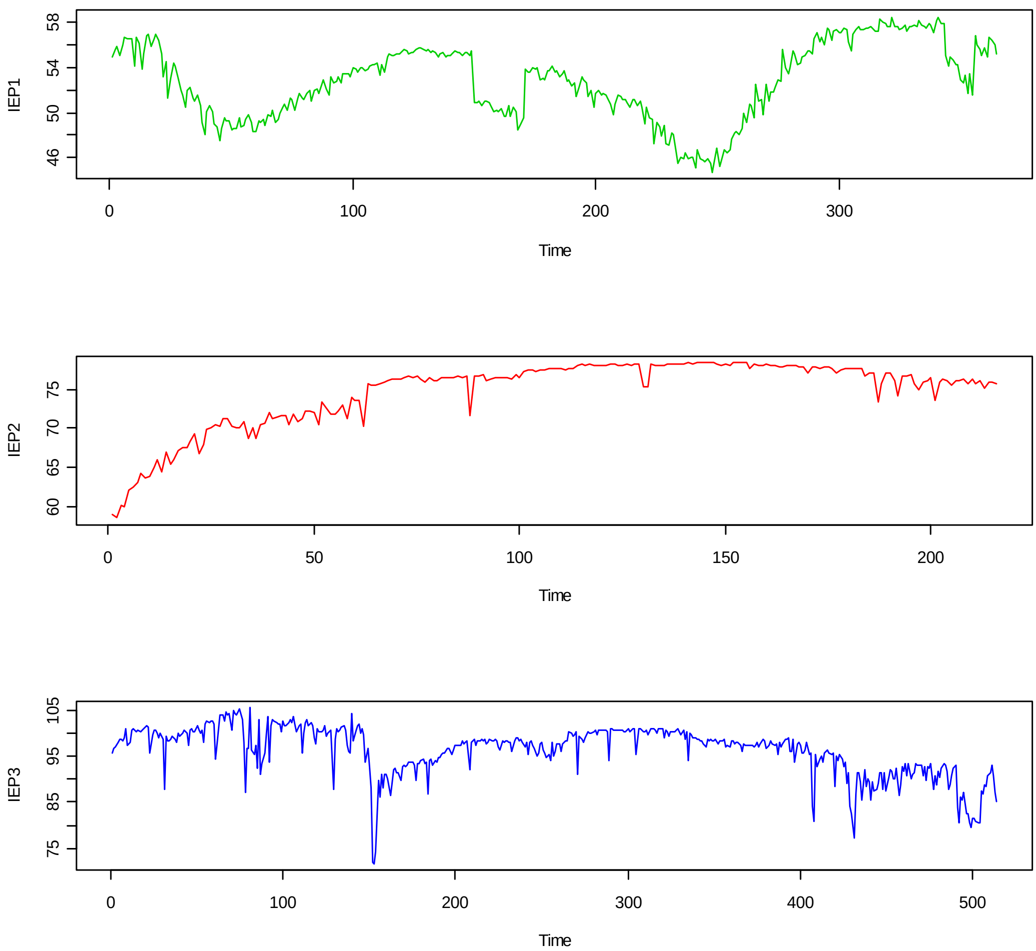


Figure 3.3: Daily Iranian electricity prices (2007-2010).

Table 3.1: Summary of descriptive statistics.

Statistics	No.Ob	Time span	Median	Min	Max	Mean	Stdev	Skewness*	Kurtosis *	Jarque – Bera test *
1st part	365 (1-365)	21/03/2007-19/03/2008	52.99	44.71	58.42	52.75	3.31	-0.294 (0.0108)	-0.78 (0.00112)	14.349 (0.0007655)
2nd part	207 (366-581)	20/03/2008-25/10/2008	76.40	55.19	78.45	74.59	4.58	-1.70 (4.316219e-25)	2.64 (1)	172.9735 (< 2.2e-16)
3rd part	515 (582-1095)	26/10/2008-20/03/2010	97.80	71.67	105.47	96.22	5.38	-1.380 (1.046741e-37)	2.46 (1)	297.371 (<2.2e-16)

Note: (*) In parentheses there is two side p-value related to each test.



Note: Green line- part one (March 21, 2007 to March 19, 2008). **Blue line-** part two (March 20, 2008 to November 25, 2008). **Red line-** part three (November 26, 2008 to March 20, 2010).

Figure 3.4: Three separate sections of the daily IEP time series.

Table 3.2: Variance in the daily IEP time series and seasonal and non-seasonal differences.

Time series	Variance in IEP1 time series after detecting outliers	Varince in IEP2 time series after taking its seasonal difference	Variance in IEP3 time series after taking first order non seasonal difference
First part of Iranian electricity Price time series	10.84422	2.731688	0.6219434
Second part of Iranian electricity price time series	20.51978	2.395583	0.8728095
Third part of Iranian electricity price time series	27.22072	19.94653	1.217683
	Variance in Iranian electricity price –Total time series		
Iranian electricity price –Total time series	397.161	7.127601	0.9770599

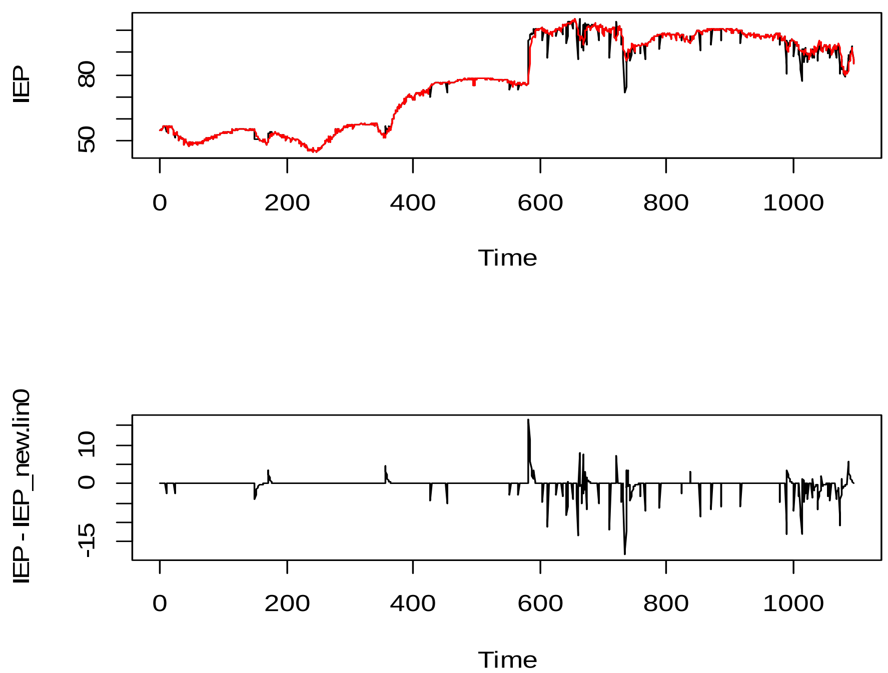


Figure 3.5: Daily Iranian electricity price time series after detecting outliers (lineraized).

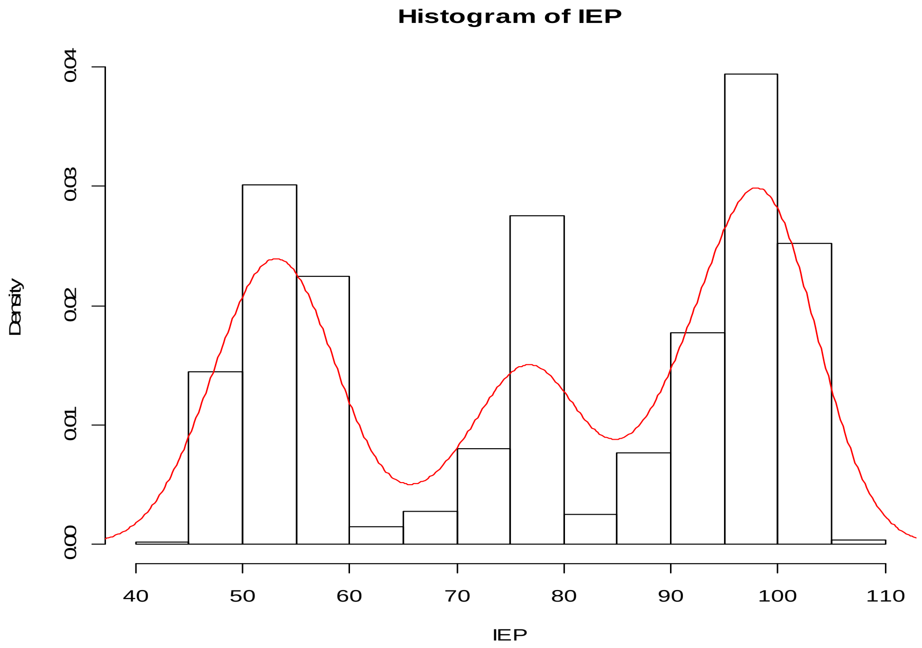
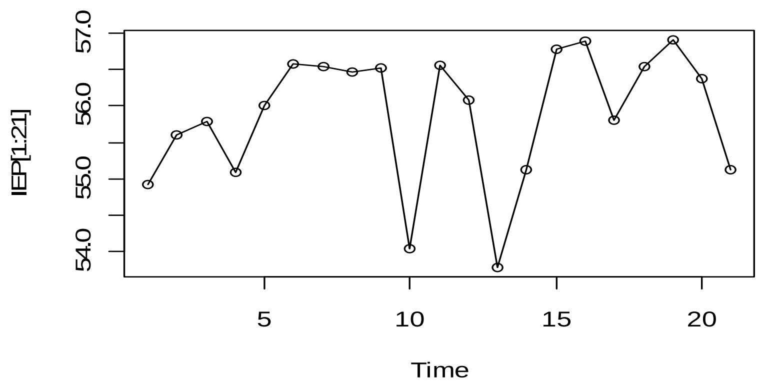


Figure 3.6: Histogram of daily Iranian electricity price (after detecting outliers).



(The first 21 days of the IEP time series).

Figure 3.7: Seasonal behavior shown in the IEP series.

Table 3.3: Augmented Dickey Fuller tests (Unit root test) after detecting outliers.

Test	1st section	2nd section	3 rd section	Whole series
ADF test for Iranian electricity price	data: IEP.lin1 Dickey-Fuller test =-2.382 p-value = 0.4157 alternative hypothesis: stationary	data: IEP.lin2 Dickey-Fuller test =-3.0949 p-value = 0.1167 alternative hypothesis: stationary	data: IEP.lin3 Dickey-Fuller test = -3.2032 p-value = 0.08739 alternative hypothesis: stationary	data: IEP.lin Dickey-Fuller = -1.25 p-value = 0.8958 alternative hypothesis: stationary

The "Augmented Dickey Fuller" (ADF) test is an extension of the Dickey and Fuller Test of 1979. It examines whether or not the time series are stationary (Tsay, 2005; Narzo, 2008; Pfaff, 2008). In this case, the null hypothesis is that the series is stationary against the alternative that it is not. In Table 3.3, the p-value derived from the ADF test is greater than 0.05 (predetermined significance level), which suggests that the whole time series and each of the sections are stationary. In other words, each section of the IEP time series may be a stationary times series, since the p-value is greater than 0.05 (Tsay, 2005; Pfaff, 2008).

On the other hand, the price series tends to exhibit a structural change for various reasons. Major policy changes or economic downturns could cause a break in the data series which might result in a change of level and/or in slope of the profile. This means the ADF test may not perform well in scenarios with such structural breaks. Here, the ADF test cannot be utilized, since the IEP exhibits structural changes in its trends, including three breakpoints. In other words, when there are structural breaks in the test data, the ADF test becomes biased towards a spurious acceptance of non-stationary behavior due to misspecification of bias and size distortions. To overcome this situation, the unit root test with structural breaks is a more appropriate tool (Pfaff, 2008).

The Zivot and Andrews Test was proposed by the statisticians of the same name in 1992. This unit root test can be used in order to take into account any existing structural breaks. The null hypotheses are defined so that there is a unit root with a drift and/or break at an unknown point against the alternative hypothesis, which is a stationary trend with a break in an intercept or a trend at an unknown point (Pfaff, 2008).

For the IEP time series, the null hypothesis here is rejected, because the test statistics value is less than the critical values at each significant confidence interval level, see Table 3.4. In conclusion, there is a trend in the time series. The R code of this test is also represented for Iranian electricity time series.

Table 3.4: Zivot and Andrews Test for the IEP time series:
(Unit Root Test for "the daily IEP time series" after detecting outliers).

Unit root results test	Critical values for 99% confidence interval level	Critical values based for 95% confidence interval level	Critical values for 90% confidence interval level
Test statistics value for Iranian electricity price time series	Critical values		
-5.6576	-5.57	-5.08	-4.82

R -code (1)- Zivot and Andrews Test Code and its results for the IEP time series.

```
za.iran=ur.za(iran.price[,1],model="both",lag=10)
summary(za.iran)
################################
# Zivot-Andrews Unit Root Test #
################################
Call: lm(formula = testmat)
Residuals:
     Min       1Q   Median       3Q      Max
-18.5111  -0.5829   0.1597   0.6932  17.7866
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.123634   0.580732   5.379 9.21e-08 ***
y.l1         0.927123   0.012719  72.892  < 2e-16 ***
trend        0.004647   0.000920   5.052 5.15e-07 ***
y.dl1       -0.297868   0.030993  -9.611  < 2e-16 ***
y.dl2       -0.128813   0.032278  -3.991 7.04e-05 ***
y.dl3       -0.190667   0.032461  -5.874 5.68e-09 ***
y.dl4       -0.058772   0.032989  -1.782  0.07511 .
y.dl5        0.004468   0.032879   0.136  0.89192
y.dl6       -0.087051   0.032921  -2.644  0.00831 **
y.dl7        0.036506   0.032948   1.108  0.26812
y.dl8       -0.046714   0.032308  -1.446  0.14851
y.dl9       -0.026445   0.031940  -0.828  0.40789
y.dl10       0.099362   0.030287   3.281  0.00107 **
du           1.850031   0.384309   4.814 1.69e-06 ***
dt          -0.007062   0.001261  -5.599 2.74e-08 ***
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 2.092 on 1069 degrees of freedom
  (11 observations deleted due to missingness)
Multiple R-squared: 0.9889,     Adjusted R-squared: 0.9888
F-statistic:  6833 on 14 and 1069 DF,  p-value: < 2.2e-16
Teststatistic: -5.7297
Critical values: 0.01= -5.57 0.05= -5.08 0.1= -4.82
Potential break point at position: 581
```

Additionally, the Autocorrelation (ACF) and Partial autocorrelation functions (PACF) have been employed (Tsay, 2005) to analyze all four time series. In general, for a stochastic process Y_t , the Autocorrelation function, $\rho_{t,s}$, is given by Eq.(3.1), where t,s= 0, ±1, ±2, etc. (Cryer, 2008):

$$\mathbf{corr}(\mathbf{Y_t},\mathbf{Y_S})=\frac{\mathbf{Cov}(\mathbf{Y_t},\mathbf{Y_s})}{\sqrt{\mathbf{Var}(\mathbf{Y_t})\mathbf{Var}(\mathbf{Y_S})}}=\boldsymbol{\rho}_{\mathbf{t,s}}$$

Eq. 3.1

Here, the $Cov(Y_{t,}Y_s)$ is defined as an Autocovariance function; for more information, see Cryer, (2008). The values of $\rho_{t,s}$ near ±1 indicate strong linear dependence, whereas values near zero, indicate weak linear dependence. If $\rho_{t,s} = 0$, we say that Y_t and Ys are uncorrelated (Cryer, 2008).

The ACF is computed in order to determine the non-stationary condition in time series: for the Y_t data sequence, this is either residuals, standardized residuals, original data, or some data transformation. The obvious way to do this is to compute the sample correlation between the k pair units, or a section in time. Therefore, we estimate the sample autocorrelation function ρ_k for a variety of k lags {k = 1, 2,…}. Here, the sample ρ_k is defined as r_k and it is given in Eq. (3.2) (Cryer, 2008):

$$r_k = \frac{\sum_{t=k+1}^{n}(Y_t - \bar{Y})\,(Y_t - \bar{Y}\ \ )}{\sum_{t=1}^{n}(Y_t - \bar{Y})}$$

Eq. 3.2

A plot of (partial) autocorrelation versus lag k is often called a correlogram in time series analysis; see (Cryer, 2008; Tsay, 2005). On the other hand, the partial correlation (PACF) also is derived from the autocorrelation function (Cryer, 2008).

The PACF determines the order of the autoregressive models (AR), while the ACF describes the order in the moving-average model (Cryer, 2008; Box et al., 2008; Tsay, 2005). In these correlograms—the partial autocorrelation and the autocorrelation functions—all values are within the horizontal dashed lines, which are placed at zero, plus and minus two. These are the approximate standard errors in sample autocorrelations. This means that with a 95% confidence interval, which is reflected as a significance level of 0.05, the autocorrelations of the observations in each lag can compare against the critical area; see Box et al., (2008).

Note that the autocorrelation function or correlogram has a wide variety of shapes; for further information on this, see Cryer, (2008). Depending on the outcome of the ACF and PACF functions, the behavior pattern of the time series can be determined. As observed in Figure 3.8-A, there is an autocorrelation in the observations over time in the three sub-time series. There is also strong serially positive autocorrelation in all lags. The resulting ACF values are slightly less unified. Overall, there is a steady decreasing trend in the autocorrelation function (the lines represent the 95% confidence intervals). This suggests that the serial correlation of the time series is significant in each lag. In other words, these time series do not show any stationary behavior. These large dependencies and correlations in the data are not solely related to time, even after detecting the outliers; they are defined as data that appears to drop significantly from the other examples of our observations, and the first difference in each time series section.

In Figure 3.8-B, some serial correlations can be found over time in some lags. As explained above, Figure 3.4 and Table 3.1 demonstrate that the IEP time series exhibit different behavior in each section of the time series. Due to weak stationary behavior in the time series analysis, the first estimate models are represented via the "autoregressive integrated moving average" or ARIMA model, which is explained in next section, and also by Tsay (2005) and Cryer (2008).

A-ACF and PACF of daily IEP (three parts). B-ACF and PACF of the first difference in the daily IEP (three parts).

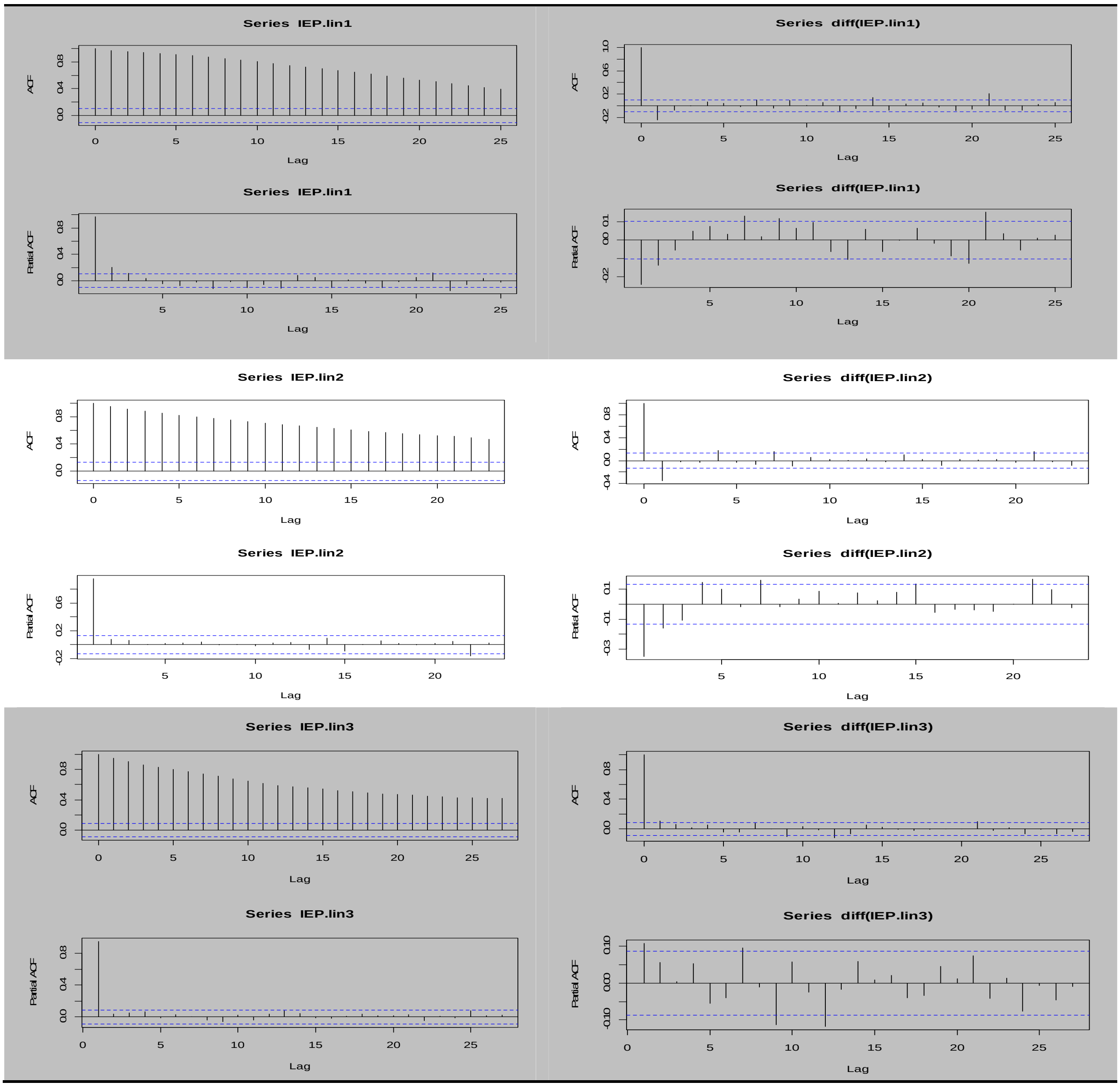


Figure 3.8: ACF and PACF functions in the three parts of the IEP time series.

3.1.2 Time series modelling of Iranian electricity prices

In this section, the most suitable model for the IEP is determined using linear and nonlinear approaches in time series analysis.

3.1.2.A ARIMA models

As explained in the last section, the researcher attempted to improve upon the stationary condition of the IEP time series by taking into account non-seasonal differences, as shown in Figure 3.8. However, after doing so, the time series demonstrated weak stationary behavior patterns during those periods. Therefore, the ARIMA model was applied in order to estimate the patterns in these time series. The general ARIMA (p,1,q)(P,D,Q)$_s$ model is presented in greater detail by Tsay (2005) and Cryer, et al., (2008), according to Eq.(3.3) (R Dahyot 2012):

$$\phi(B)\Phi(B^S)(1-B^d)\ (1-B^D)\ Yt=\Theta(B^S)\theta(B)e_t \qquad \text{Eq. 3.3}$$

Here, "Y_t"is introduced as a dependent variable defined as the IEP at time t, which depends on the price as of the previous time. Variables B and B^S are introduced as a backshift parameter operator (Box et al., 2013). The "s" represents the period of seasonality in ARIMA models. The t-value is calculated as the coefficient / standard error of the estimated parameter. The "ϕ" coefficients are associated with the autoregressive section (AR), while "p" determines the AR order to be used in the arranged auto regression. "θ" is related to MA (Moving Average section in the ARIMA model) and q indicates the order of the MA section.

Table 3.5: Estimated ARIMA models for the daily IEP time series.

Model for	ARIMA model for three parts of daily Iranian electricity Price time series

First part (1:365)	**R-code(2):** `arima(x=IEP.lin1,order=c(2, 1, 0,seasonal=list(order =c(1, 0, 1),period = 7))`
	`Coefficients:`
	`ar1 ar2 sar1 sma1`
	`-0.2635 -0.1402 0.7585 -0.6368`
	`s.e. 0.0527 0.0528 0.1296 0.1524`
	`sigma^2 estimated is 0.5525: log likelihood = -408.74, aic = 827.49`

Second part (366:581)	**R-code(3):** `arima(x=IEP.lin2,order=c(4, 1, 0),seasonal=list(order=c(0,0,1),period= 7), fixed = c(NA, NA, 0, NA, NA))`
	`Coefficients:`
	`ar1 ar2 ar3 ar4 sma1`
	`-0.3595 -0.1268 0 0.1835 0.1412`
	`s.e. 0.0668 0.0667 0 0.0645 0.0665`
	`sigma^2 estimated is 0.5082: log likelihood = -232.54, aic = 475.07`

Thrird part (581:1095)	**R-code(4):** `arima(x=IEP.lin3,order =c(1, 1, 1),seasonal=list(order = c(1, 0, 0), period = 7))`
	`Coefficients:`
	`ar1 ma1 sar1`
	`0.5911 -0.4749 0.1051`
	`s.e. 0.1905 0.2025 0.0467`
	`sigma^2 estimated is 1.318: log likelihood = -800.43, aic = 1608.86`

The "Φ" parameters are associated with B^s, which is in turn related to the seasonal AR section of the model. "p" and "q" indicate the order of the AR and MA section estimations, respectively. The "Θ" parameters are related to B^s, which is associated with the seasonal MA section (Tsay, 2005; Cryer, 2008; Dahyot, 2012). On the other hand, "d" and "D" (D is for the seasonal sections) indicates the order of the difference. The ARIMA models for the three sections of the IEP time series are described as follows:

- In the first part of the time series, the estimated model is an ARIMA (2, 1, 0)(1,0,1)$_7$. Based on Table 3.5 or Table 3.6, the first section of the IEP series model does not have an MA section in the ARIMA model. The t -values related to the estimated parameters of the Autoregressive section (with p = 2) are greater than 2 in Table 3.5. The parameters associated with the seasonal AR section of the model (P=1) and seasonal MA section (Q=1) are significant since the t-value is greater than 2. Therefore, the parameters are significant for the ARIMA models.

Table 3.6: Statistical equation of the ARIMA estimated model for IEP time series.

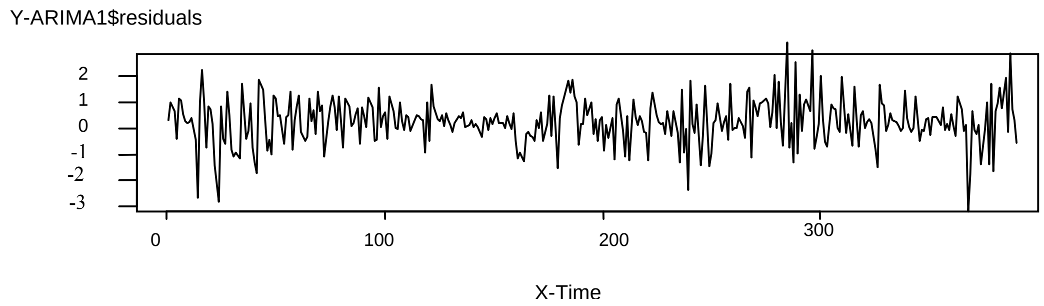
	Statistical equation of ARIMA Models for three sections of IEP	MSE
First part	$(1+0.2635B_1+0.1402B_2)(1-0.7585B_1^7)Y_t=(1-0.6368B_1^7)e_t$	0.5509449
Second part	$(1+0.3595B_1+0.1268B_2-0.1835B_4)Y_t=(1+0.1412B_1^7)e_t$	0.505876
Third part	$(1-0.5911B_1)(1-0.1051B_1^7)Y_t=(1-0.4749B_1)e_t$	1.315861

- In the second section, both parameters related to the AR section model and those of the seasonal MA section are considered to be significant.
- The ARIMA model for the third section has AR and MA parameters, as shown in Table 3.5, where the seasonal AR section also is significant. In order to investigate the validation of model, the L-jung Box Test presented by Box and Pierce (1970) clearly indicates that the individual residuals are not correlated in Table 3.7, where the p-value is more than 0.05, meaning the null hypothesis cannot be rejected (Cryer, 2008; Tsay, 2005). In Table 3.6, the mean square error was calculated for each estimated ARIMA model; see Wei (2005).

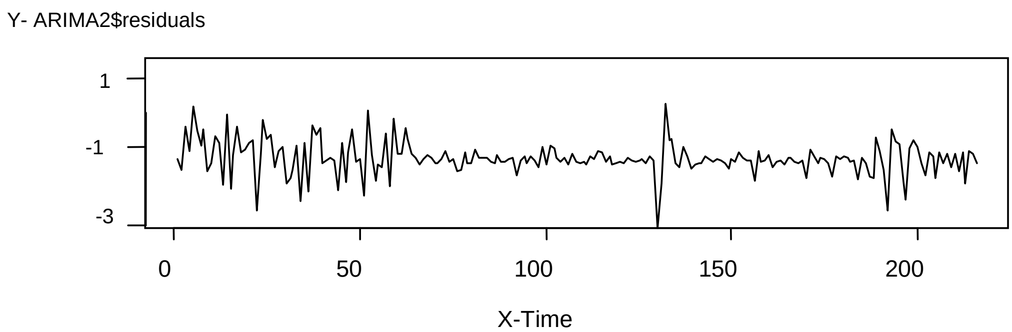
Table 3.7: Box-Test for residuals of the three ARIMA Models.

Test	First part of time series	Second part of time series	Third part of time series
Box.test For IEP time series	Box-Ljung test data: m1_priceIran$residuals X-squared = 16.5697, df = 10, p-value = 0.08444	Box-Ljung test data: m2_priceIran$residuals X-squared = 8.6743, df = 10, p-value = 0.5633	Box-Ljung test data: m3_priceIran$residuals X-squared = 12.8629, df = 10, p-value = 0.2314

Part One: Residuals of the ARIMA model related to the first part of the IEP time series.



Second part: Residuals of the ARIMA model related to the second part of the IEP time series.



Part Three: Residuals of the ARMA model related to the first part of the IEP time series.

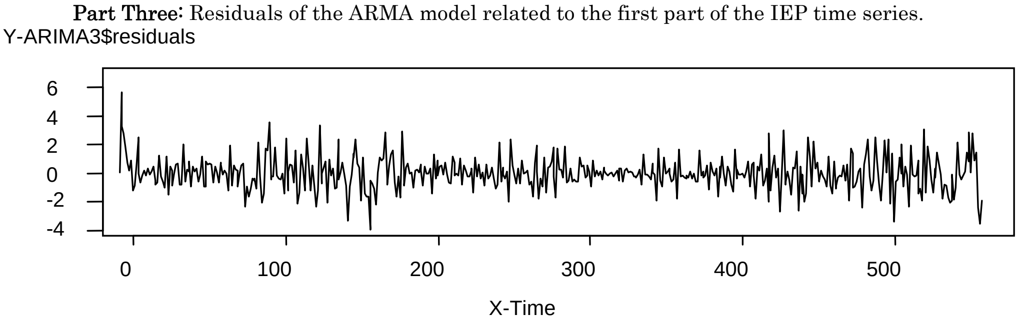
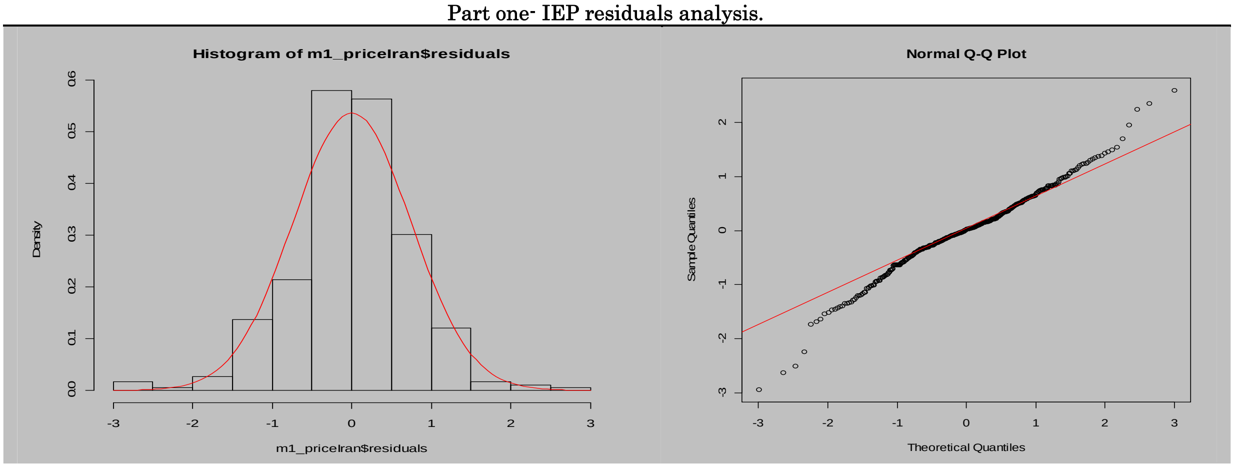


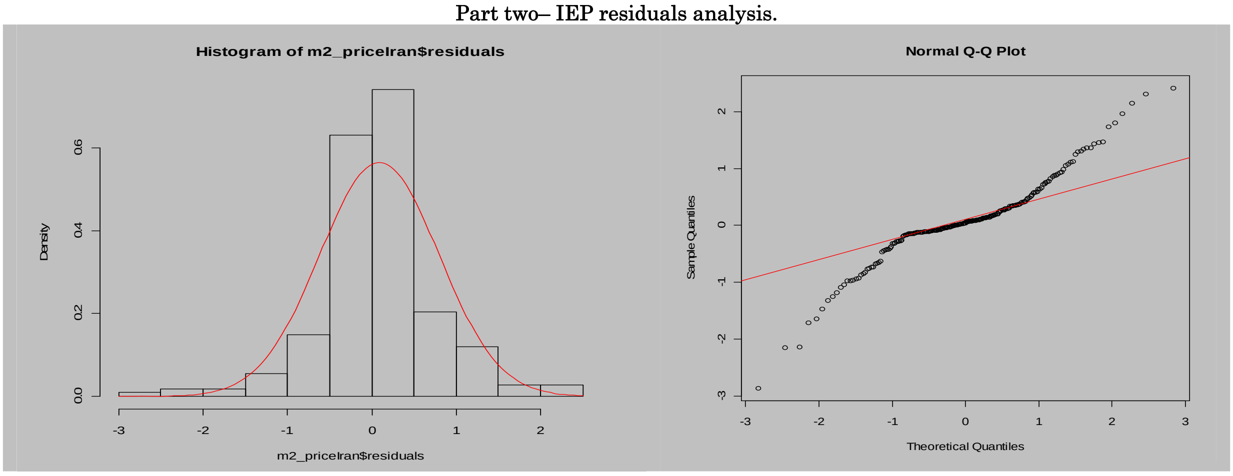
Figure 3.9: Residual behavior in all the ARIMA models.

The residual analysis of these estimated ARIMA models show that they are not fitted models. The Q-Q plots and histogram of residuals from three ARIMA models, heavy tails exist in Figure 3.10-all parts. This suggests the existence of volatility clustering in the residuals of these series(Figure 3.9-all parts) (Tsay 2005; Hu, 2011).The PACFs and ACFs of squared residuals for each sub time series (of Iranian electricity price time series) are shown in Figure 3.11-all parts prove this claim. We observe serial correlations in the residuals(Tsay, 2005; Hu,2011). Volatility is an important factor in trading and financial market time series analysis(Tsay, 2005). So, due to conditional forecasting and temporal fluctuations of the data-variance, ARIMA models are not able to accurately analyse the time series (Tsay, 2005; Wurtz et al., 2006; Cryer, 2008). Further, we navigated some introductory consideration to recognize the fitness models competency to exactly approximate the time series behaviour. In other hands, the Iranian electricity price does not show an independent and identical distribution in Figure 3.6. This situation points to nonlinear behaviour in this time series. The BDS test, which is presents in following pages, verifies this claim, see Table 3.8.

Part one- IEP residuals analysis.



Part two– IEP residuals analysis.



Part three– IEP residuals analysis.

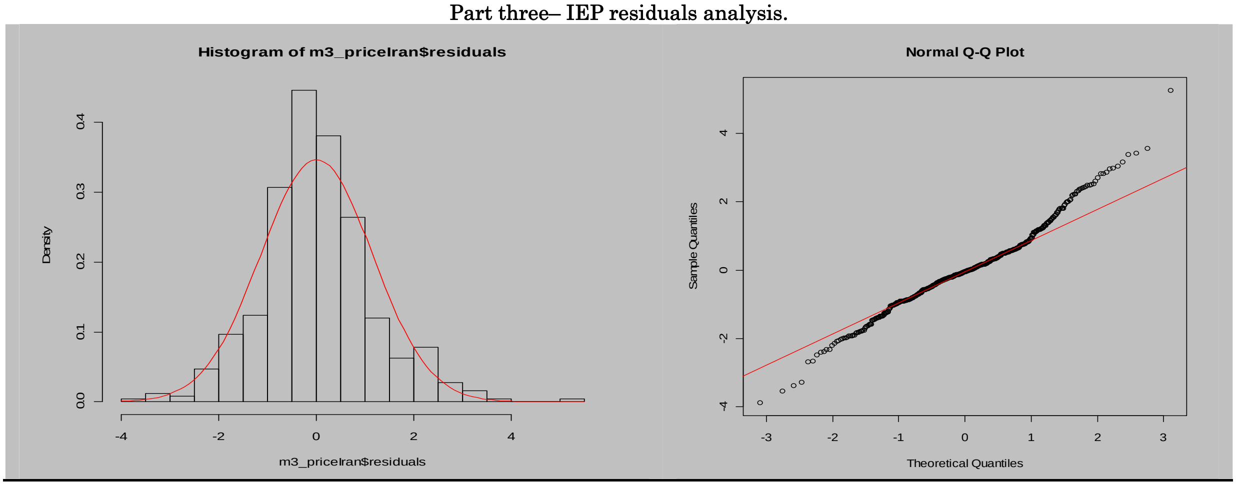
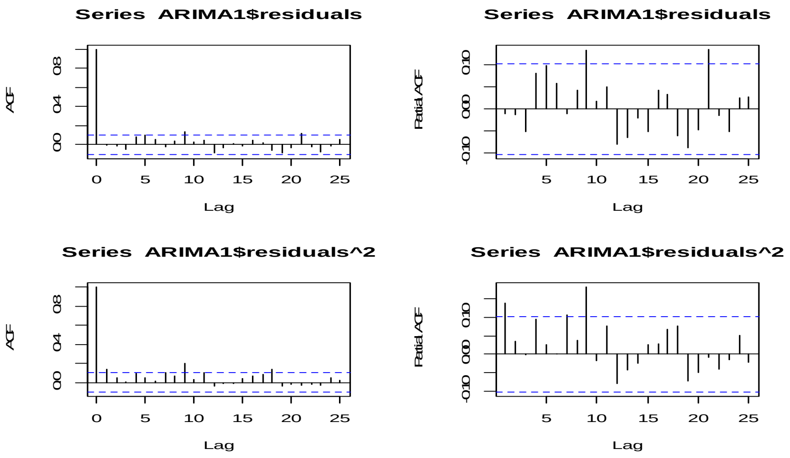
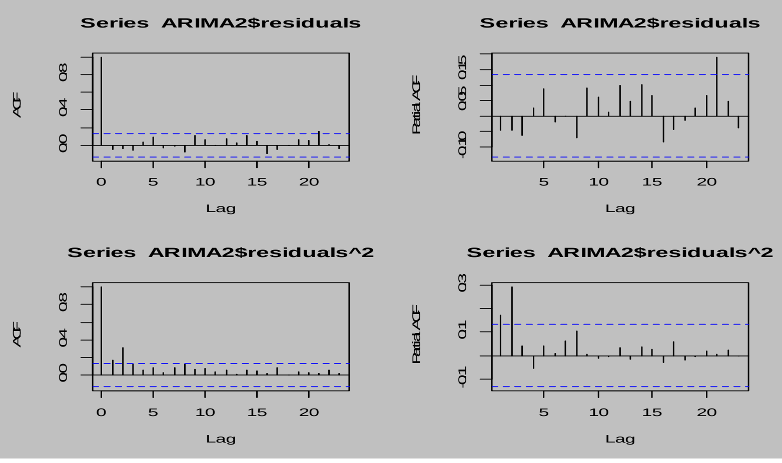


Figure 3.10: Histogram and Q-Q plot of the residuals of three ARIMA models (for the IEP time series).

Part One- Residuals analysis of the IEP ARIMA model.



Part Two- Residuals analysis of IEP ARIMA model.



Part Three –Residuals analysis of the IEP ARIMA model.

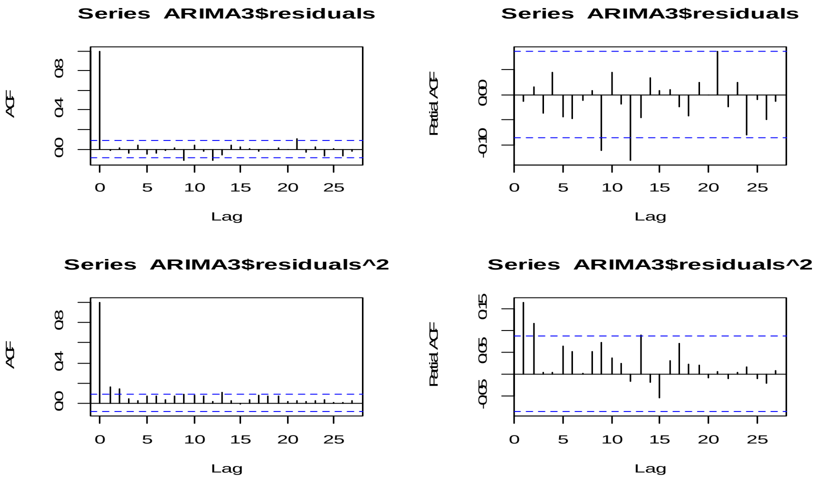


Figure 3.11: The ACF and PACF of (regular and squared) residuals in the ARIMA models.

The BDS test developed by Brock, Dechert, Scheinkman in 1987 (and later published by Brock, Dechert, Scheinkman and LeBaron in 1996) is arguably the most popular test for evaluating nonlinearity (Zivot and Wang, 2006; Wuertz, 2013). It was originally designed to test for the null hypothesis of independent and identical distribution for the purpose of detecting non-random chaotic dynamics. The main concept behind the BDS test is calculating the correlation integral of the embedding dimension m. The null hypothesis is defined so that the time series is independently and identically distributed or IID (Zivot and Wang, 2006).

In Table 3.8, since the p-value, in five combinations of the IEP price time series, is less than 0.05, the null hypothesis can be rejected. Therefore, the time series is not uniquely IID (Zivot and Wang, 2006). This suggests the time series has a nonlinear pattern. It is then necessary to employ other time series modelling approaches for evaluating price behavior in the Iranian electricity market. Consequently, nonlinear approaches in time series analysis have been introduced, explained in the upcoming sections, in order to investigate the treatment of the IEP time series.

Table 3.8: "BDS Test" for the daily IEP time series.

Test	For daily Iranian electricity price time series
BDS.test	R-code(5): bds.test(IEP_new.lin0) BDS Test data: IEP_new.lin0 , Embedding dimension = 2 3 p-value = [9.9644] [19.9289] [29.8933] [39.8578] [2] 0 0 0 0 [3] 0 0 0 0

3.1.2.B Nonlinear estimated model

The "SETAR Test" (Hansen, 1999), which identifies linearity against threshold (Narzo, 2008), proves there is no pattern of linearity in the time series. It further suggests that the time series can be represented by any arbitrary threshold yielding an Autoregressive (TAR) threshold model (Tsay, 2005). Table 3.9 shows that the p-value is less than 0.05, which indicates that the null hypothesis is a linear AR, as opposed to the alternative hypothesis, where the TAR threshold (with one or two regimes) is rejected (Narzo et al., 2008). This concludes that nonlinearity behavior exists in the time series.

Table 3.9: "SETAR Test" for the daily IEP time series.

Test	p-value	Result test
Linear AR versus 1 threshold TAR (Test 1vs2)	0	68.69868
Linear AR versus 2 threshold2 TAR (Test 1vs3)	0	138.53881
1 threshold TAR versus 2 threshold2 TAR (Test 2vs3)	0	65.6814

As discussed previously, different parts of the IEP time series exhibit different behavior patterns; see Figures 3.3 and 3.4. In addition, "asymmetry in rising patterns" in the IEP time series can help estimate the parameters associated with the time series, based on the SETAR (Self-Exciting Threshold Autoregressive) model (Tsay 2005; Chan, 2004; Boero and Marrocu, 2004).This model is specifically designed to address several nonlinear characteristics commonly observed in practice, such as asymmetry in the declining and rising patterns of a process (Tsay, 2005). Piecewise linear models are used to obtain a better approximation of the conditional mean equation. However, in contrast to the traditional piecewise linear model that allows for model changes to occur in the "time" space, the TAR model uses threshold space to improve linear approximation" (Tsay, 2005).

"The basic idea of TAR models is that the behavior of a process is described by a finite set of linear auto regression models. The appropriate AR model generates the value of the time series at each point in time; it is determined by the relation of a conditioning variable to the threshold values. If the conditioning variable is a dependent variable to itself after some delay d (y_{t-d}), the model is known as a self-exciting threshold autoregressive (SETAR) model."

"The SETAR model is piecewise-linear in the space of the threshold variable, rather than in time. An interesting feature of SETAR models is that the stationary y_t does not require in each regime, on the contrary, the limit cycle behavior of this class of models. What these models are able to describe arises from the alternation of explosive and contractionary regimes" (Tsay, 2005).

As explained above, the IEP time series exhibits nonlinear behavior. As shown in Figure 3.3, the existence of the aforementioned breakpoints clearly suggests that there are threshold values. Therefore, the SETAR model may represent estimates of the behavior of this market price more accurately.

Here, two SETAR models are represented with 2 and 3 regimes, for the sake of comparison; see Table 3.10. The constants obtained for the low regime are not significant in either case (Tsay 2005). However, other estimated parameters seem to play an important role in both cases. As a result, this model is adopted to estimate the behavior of the IEP time series.

In general, the statistical equation in the theoretical SETAR model (in the k-regime) is defined in Eq. (3.4) (Boero and Marrocu, 2004). Here, K is the number of regimes, d is the delay parameter, and p_t is the autoregressive order in the ith regime of the model. The threshold parameters satisfy the constraint $-\infty=r_0<r_1<r_2<\ldots<r_{k-1}<r_k=\infty$, the innovation within the ith regime "e_t^i" is a IID sequence having normal random variables with a mean of zero and a constant variance of $\sigma_i^t < \infty (i = 1,2,\ldots,k)$. If homoscedasticity is assumed across the regime (i,e.,$\sigma_1^2 = \sigma_2^2$=........=σ_k^2=σ_i^2), the common variance σ_i^2 can be estimated by the sample pooled variance in the data.

The model superscripts indicate states of the world or regimes. Within each regime, it is assumed that the dynamic behavior of the time series variable follows a linear autoregressive process. The regime operative at the time "t" depends on the observable past history of $\{y_t\}$, in particular, on the value of $y_{t\text{-}d}$, resulting in Eq. (3.4) (Chan et al., 2004).

$$\mathbf{SETAR-k: y_t} = \begin{cases} \emptyset_0^{(1)} + \sum_{j=1}^{p^{(1)}} \emptyset_j^{(1)} y_{t-j} + e_t^{(1)} & \text{if } y_{t-d} \le r_1 \\ \emptyset_0^{(2)} + \sum_{j=1}^{p^{(2)}} \emptyset_j^{(2)} y_{t-j} + e_t^{(2)} & \text{if } r_1 < y_{t-d} \le r_2 \\ \vdots & \\ \emptyset_0^{(k)} + \sum_{j=1}^{p^{(k)}} \emptyset_j^{(k)} y_{t-d} + e_t^{(k)} & \text{if } r_{k-1} < y_{t-d} \end{cases}$$

Eq. 3.4

For the given values of d and r, separate AR models are fitted to the appropriate data subsets, the order of each model being chosen according to normal AIC criteria. In the second stage, r can vary over a set of possible values while d must remain fixed; the re-estimation of the separate AR models allows for the determination of the r parameter, as the one in which the AIC(d) attains its minimum value. In stage three, the search over d is carried out by repeating both stages one and two for d=d_1, d_2,…,d_p. The selected value of d is, again, the value that minimizes the AIC(d) (Boero and Marrocu, 2004).

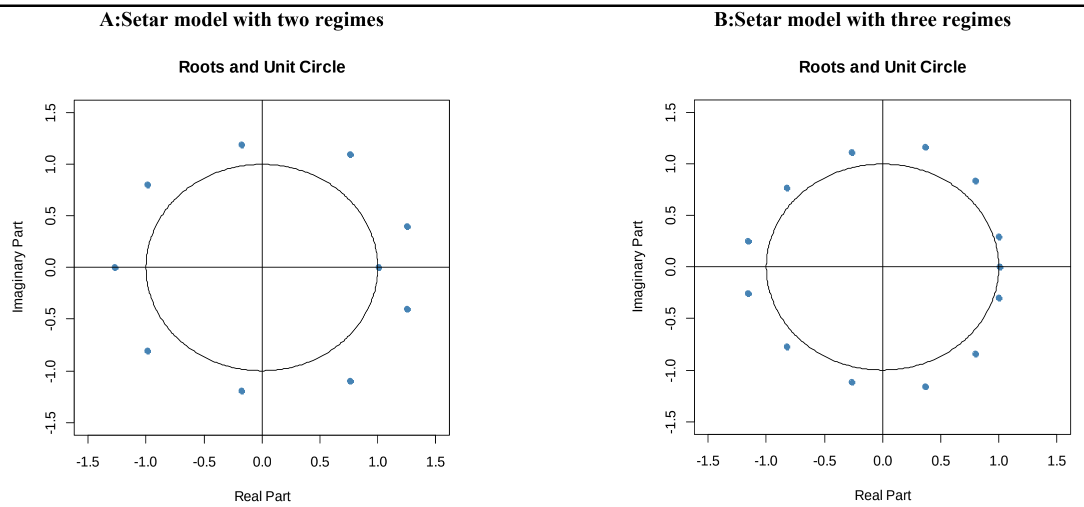


Figure 3.12: The roots and Unit circle results for both SETAR models.

In this case, the two SETAR models are initially compared with two and three regimes, which can be represented as follows.

These models are presented in Table 3.10, where "e_t" is assumed to be IID (0, $\sigma^{2(k)}$), following Eq. (3.4), and 75.71 indicates the threshold value for the first model (with two regimes) while the values of 75.71 and 95.27 are employed in the second model with three regimes (Chan et al., 2004). The results found in Table 3.11 also suggest that all coefficients (and/or the estimated parameters) excluding "Phil.3" are insignificant for the first model-two regimes, because the p-value is greater than 0.05.

In addition, one of the coefficients is greater than one which, as discussed before, does not necessarily indicate no unit roots are being observed.

The roots and the unit circle plot are more clearly expressed in Figure 3.12 (Magnus, Jan R.; Rothenberg, 1988) (Pfaff, 2008). In Table 3.10, the MSE is evaluated in each estimated SETAR model).

Table 3.10: Estimated SETAR models with two and three regimes

```
SETAR model( K=2 regimes): Non linear autoregressive model
R-Code(6):
iran.setar1O=setar(IEP_new.lin0,m=14,nthresh=1,mL=14,mH=14,
ML=c(1:4,14),MH=c(1,5,7,9,10),thDelay=1)
summary(iran.setar1O)
```

```
Coefficient(s):
Estimate  Std. Error  t value  Pr(>|t|)
const L -0.143037    0.373194  -0.3833 0.7015893
phiL.1   0.629941    0.056284  11.1922 < 2.2e-16 ***
phiL.2   0.187352    0.065371   2.8660 0.0042378 **
phiL.3   0.115082    0.066446   1.7320 0.0835665.
phiL.4   0.147765    0.060821   2.4295 0.0152814 *
phiL.14 -0.076544    0.022112  -3.4617 0.0005577 ***
const H  0.792664    0.389782   2.0336 0.0422347 *
phiH.1   1.045803    0.016866  62.0053 < 2.2e-16 ***
phiH.5  -0.098282    0.031257  -3.1443 0.0017103 **
phiH.7   0.091386    0.036365   2.5130 0.0121150 *
phiH.9  -0.154714    0.045048  -3.4344 0.0006163 ***
phiH.10  0.107308    0.036216   2.9630 0.0031133 **

Threshold Variable: Z(t) = + (0) X(t) + (1) X(t-1)+ (0) X(t-2)+ (0) X(t-3)+ (0) X(t-4)+ (0)
X(t-5)+ (0) X(t-6)+ (0) X(t-7)+ (0) X(t-8)+ (0) X(t-9)+ (0) X(t-10)+ (0) X(t-11)+ (0) X(t-
12)+ (0) X(t-13)    , Value: 75.71
```

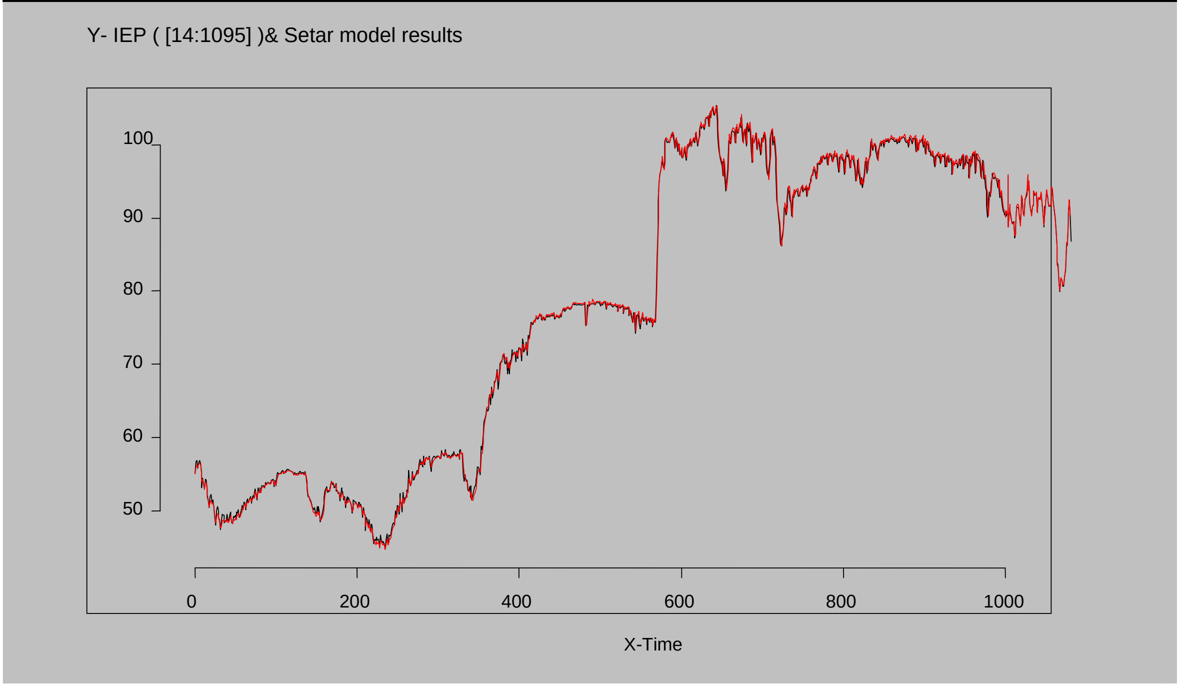
```
SETAR model ( K=3 regimes) : Non linear autoregressive model
R-Code(7):
iran.setar2O=setar(IEP_new.lin0,m=14,nthresh=2,mL=14,mH=14,mM=14,
ML=c(1:4,14),MM=c(1,3,9,10,12,13),MH=c(1,7,8),thDelay=1)
summary(iran.setar2O)
```

```
Coefficient(s):
         Estimate  Std. Error  t value  Pr(>|t|)
const L -0.143037    0.363540  -0.3935 0.6940606
phiL.1   0.629941    0.054828  11.4894 < 2.2e-16 ***
phiL.2   0.187352    0.063680   2.9421 0.0033299 **
phiL.3   0.115082    0.064728   1.7779 0.0756942.
phiL.4   0.147765    0.059248   2.4940 0.0127795 *
phiL.14 -0.076544    0.021540  -3.5536 0.0003964 ***
const M  0.726235    0.617432   1.1762 0.2397671
phiM.1   1.171416    0.031954  36.6592 < 2.2e-16 ***
phiM.3  -0.195250    0.039192  -4.9819 7.331e-07 ***
phiM.9  -0.161382    0.058427  -2.7621 0.0058401 **
phiM.10  0.143710    0.067523   2.1283 0.0335378 *
phiM.12 -0.159518    0.066582  -2.3958 0.0167543 *
phiM.13  0.192714    0.053355   3.6119 0.0003179 ***
const H  6.223413    2.368070   2.6281 0.0087095 **
phiH.1   0.905474    0.028218  32.0889 < 2.2e-16 ***
phiH.7   0.213752    0.052180   4.0964 4.510e-05 ***
phiH.8  -0.182465    0.045895  -3.9757 7.486e-05 ***

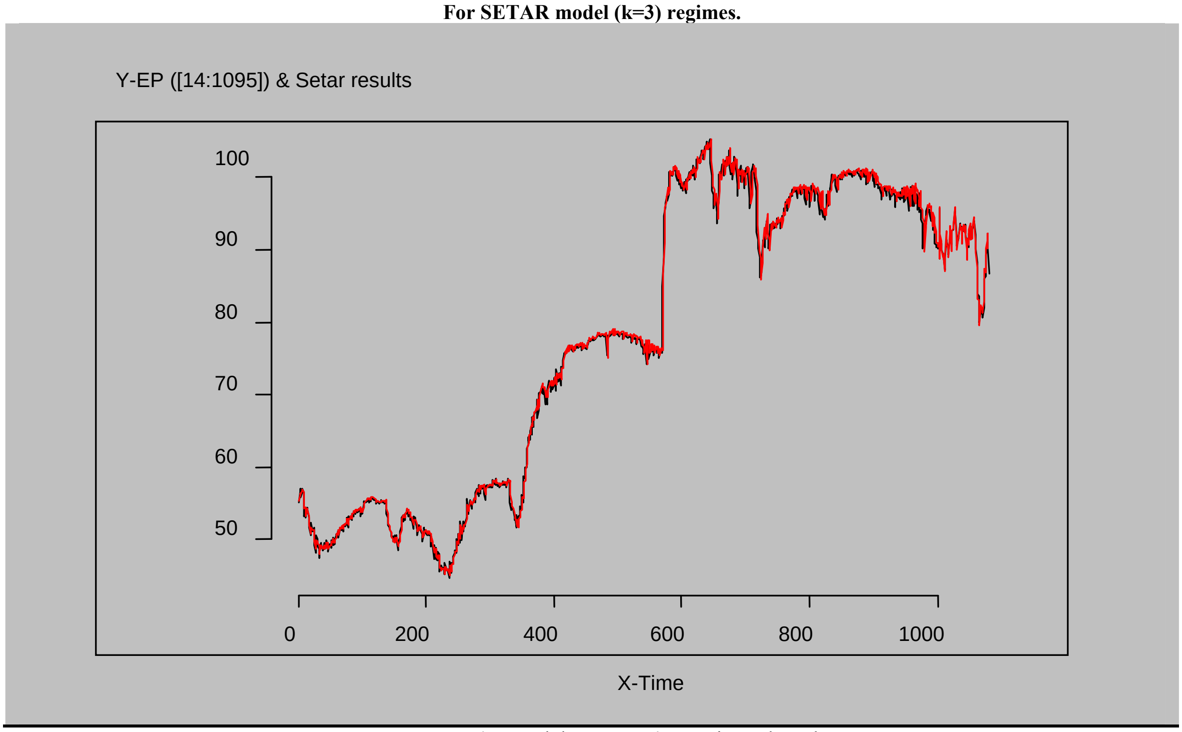
Threshold Variable: Z(t) = + (0) X(t) + (1) X(t-1)+ (0) X(t-2)+ (0) X(t-3)+ (0) X(t-4)+ (0)
X(t-5)+ (0) X(t-6)+ (0) X(t-7)+ (0) X(t-8)+ (0) X(t-9)+ (0) X(t-10)+ (0) X(t-11)+ (0) X(t-
12)+ (0) X(t-13)   , Value: 75.71 95.27
```

Note: These models are fitted for the whole daily IEP time series.

For SETAR model (k=2) regimes.



For SETAR model (k=3) regimes.



Note: Black line: real data. **Red Line:** estimated results.

Figure 3.13: Overlapping experience (or real) data with estimated results of the SETAR models.

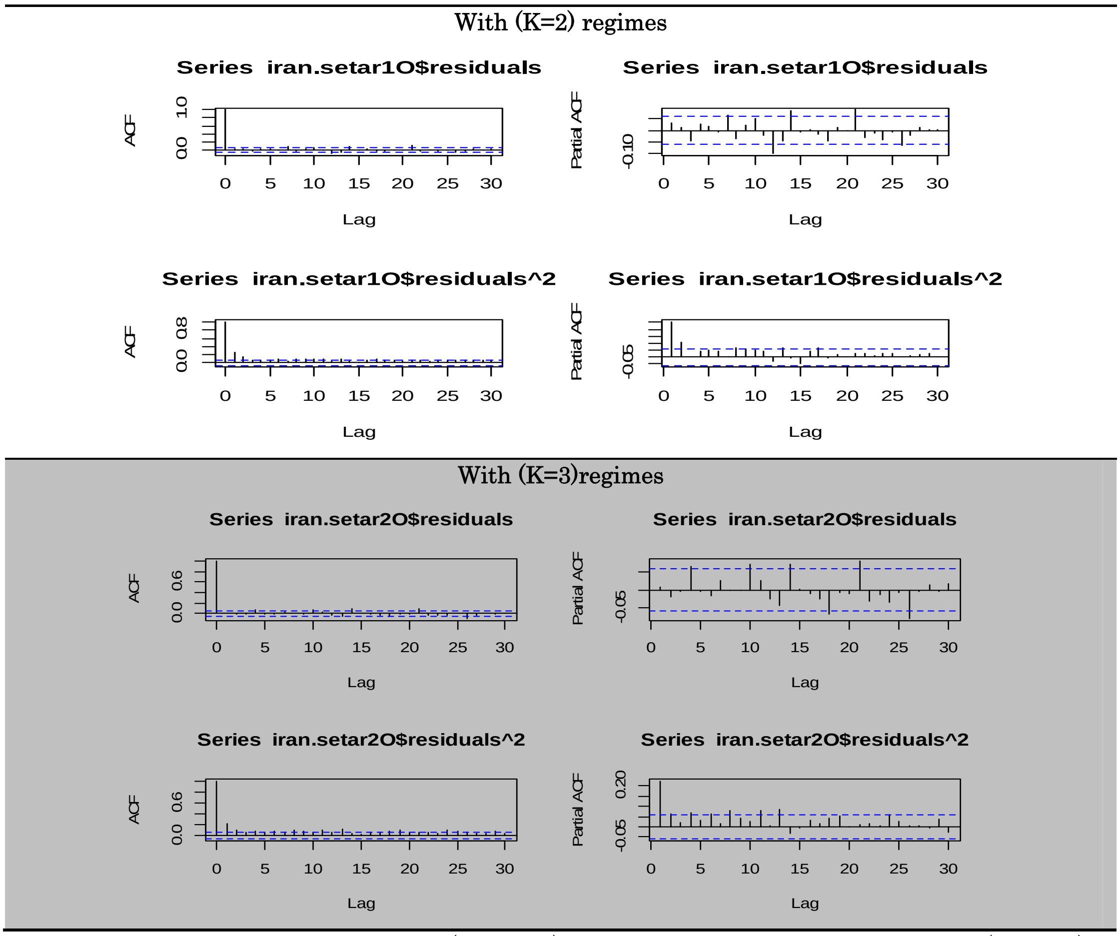


Figure 3.14: ACF and PACF of the (squared) residuals from the SETAR models (K=2&3).

In Figure 3.13, the data is compared against the estimated results of the SETAR models, which clearly suggests that these models may be usable in estimating the behavior of the IEP in this market. However, some points are near to one, which may indicate the existence of a unit root in these models (Figure 3.12). On the other hand, any temporal dependency sequence of residuals has been estimated in the current model using autocorrelation (ACF) and partial correlation functions (PACF) in the SETAR models.

In Figure 3.14, some serial correlations have been identified within the residuals of the SETAR models. In addition, the histogram and the Q-Q plot in Figure 3.15 concerning these residuals indicate large, heavy tails. Hence, these results also directly lead to the evidence of volatility clustering amongst the residuals of these models.

In conclusion, to calculate a suitable model that takes into account all the aforementioned conditions and parameters, once again the research points to the examination of other models, such as the ARMA-GARCH. These comparisons are re-formed in order to determine the best possible model within other scenarios

Table 3.11: Statistical equation of SETAR models
with two and three regimes for the daily IEP time series.

Model	Statistical equation of SETAR models	MSE
Setar model with two regimes	$price_{\,t} = \begin{cases} -0.629941price_{t-1} + 0.187352\ price_{t-2} + 0.115082\ price_{t-3} + 0.147765\ price_{t-4} - 0.076544\ price_{t-14} & price_{t-1} < 75.71 \\ 1.045803price_{t-1} - 0.098282price_{t-5} + 0.091386price_{t-7} - 0.154714\ price_{t-9} + 0.107308\,price_{t-10} & price_{t-1} > -75.71 \end{cases}$	0.8613
Setar model With three regimes	$price_{\,t} = \begin{cases} -0.629941price_{t-1} + 0.187352\ price_{t-2} + 0.115082\ price_{t-3} + 0.147765\ price_{t-4} - 0.076544\ price_{t-14} & price_{t-1} < 75.71 \\ -0.195250\ price_{t-3} - 0.161382\,price_{t-9} + 0.143710\,price_{t-10} - 0.159518\,price_{t-12} + 0.19271\ price_{t-13} & 75.71 < price_{t-1} < 95.2 \\ 6.223413 + 0.905474price_{t-1} - 0.213752price_{t-7} - 0.182465price_{t-8} & price_{t-1} > 95.27 \end{cases}$	0.9118

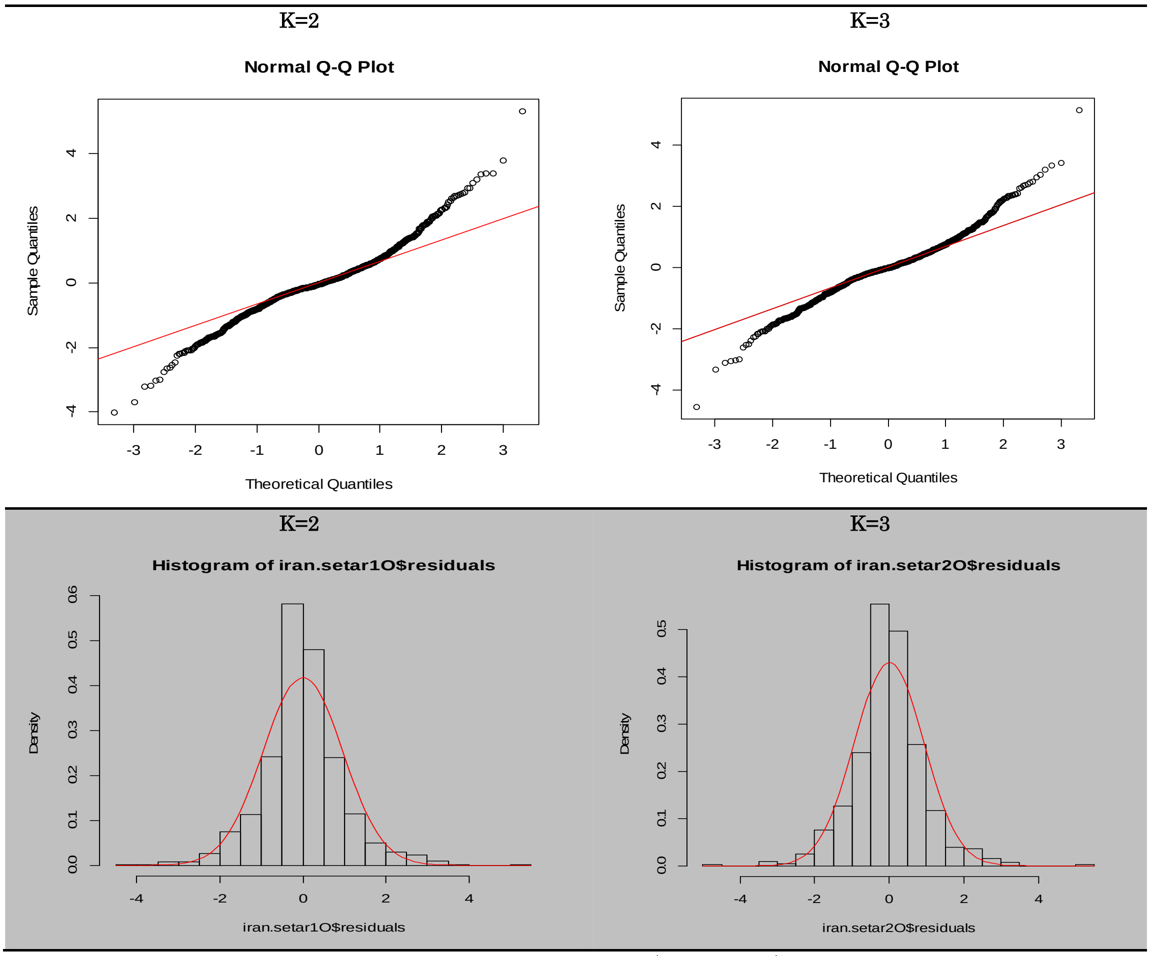


Figure 3.15: Residuals analysis of the SETAR models (K=2 and3) via a Q-Q plot and histogram.

3.1.2.C ARMA-GARCH model

Volatility is an important factor in trading and financial market time series analysis (Tsay, 2005). Benini, et al., (2002) explained that the volatility of electricity markets in general depends on a large number of parameters and factors. In particular, electricity price volatility is caused by demand elasticity and variations, fuel prices, currency exchange rates, the availability of generating units, etc. (Benini, et al., 2002).

The ARMA-GARCH models are usually referred to as conditional heteroscedastic (or non-constant variance) models. These models are used to analyze datasets having uncertainty and temporal oscillations that may cause conditional predictions of the data variance; see references (Cryer et al., 2008; Tsay 2005; Wurtz et al. 2006). In general, the GARCH model can be understood as a specialized type of ARCH model. The residuals obtained by the ARIMA and nonlinear models clearly indicate correlations between residuals and non-constant variance (Wurtz et al. 2006; Tsay 2005; Cryer et al., 2008).

Volatility is an important factor when considering the IEP time series. As discussed before, when there is uncertainty (heteroscedasticity) due to temporal fluctuations and conditional predictions of the data-variance, the ARIMA models and the SETAR model are not able to accurately analyze the IEP time series. Some preliminary investigations were conducted to assess the suitability of models and their capability to accurately estimate time series behavior, including the ARMA-GARCH model. As shown in the previous section, due to existence of heteroscedasticity and temporal fluctuations, ARMA-GARCH models were proven to be suitable for demonstrating the time series behavior patterns (Tsay, 2005). By defining μ_t and the standard deviation σ_t in the time series, the resulting Equations (3.5) and (3.6) are:

$$\mu_{t=}\mathbf{E}(\mathbf{r_t}|\mathbf{F_{t-1}}) \qquad \text{Eq. 3.5}$$

$$\boldsymbol{\sigma}^2=\mathrm{Var}\ (\mathbf{r^t}|\mathbf{F_{t-1}}) = \mathbf{E}\left[(\mathbf{r_t}-\boldsymbol{\mu_t})^2|\mathbf{F_{t-1}})\right] \qquad \text{Eq 3.6}$$

The ARMA-Garch models are defined as:

$$r_t = \mu + \sum_{i=1}^{p} \varphi_i r_{t-1} + \sum_{j=1}^{q} \theta_j a_{t-j} + a_t \qquad \text{Eq.3.7}$$

$$a_t = \sigma_t \varepsilon_t$$

$$\boldsymbol{\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-1}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-1}^2 + a_t}$$

Eq 3.8

Here, "r_t" is introduced as the conditional mean plus the white noise series in Eq. (3.7). The return "r_t" follows the ARMA (p,q) section of the ARMA-GARCH model. "a_t" is introduced as one parameter of the GARCH model in Eq.(3.8), which is the noise term in one standard ARMA part of model (Tsay 2005; Wurtz et al. 2006). Here, the Gaussian white noise with unit variance is introduced by parameter "ε_t", which is also hoped to be an aggregation of the α and ß in Eq. (3.8), which will be less than 1. Coefficients α and ß should be positive in order to be stationary with a finite variance (Tsay, 2005; Wurtz et al., 2006; Zhang, 2009). The parameters "σ_t^2" are related to the conditional variance and heteroscedasticity; for further details, see (Tsay, 2005; Wurtz et al., 2006; Zhang, 2009). In Table 3.12, the estimated ARMA-GARCH Model for the overall daily IEP is included in Table 3.12.

Table 3.12: Estimated ARMA-GARCH model for the entire IEP time series.

```
                  Title:GARCH Modelling for daily Iran electricity price time series.
R-code(8):
garchFit(formula =~arma(7, 1)+garch(1, 1),data= IRAN,trace = F)
Error Analysis:
Estimate   Std. Error   t value Pr(>|t|)
mu         0.07665      0.06467    1.185   0.2359
ar1        1.00000      0.14753    6.778 1.22e-11 ***
ar2       -0.03456      0.12274   -0.282   0.7783
ar3        0.03881      0.03467    1.119   0.2630
ar4        0.05847      0.03442    1.699   0.0893 .
ar5       -0.03309      0.04597   -0.720   0.4716
ar6       -0.04047      0.04521   -0.895   0.3707
ar7        0.18860      0.04474    4.216 2.49e-05 ***
ar8       -0.17889      0.03027   -5.910 3.43e-09 ***
ma1       -0.23817      0.15114   -1.576   0.1151
omega      0.06131           NA       NA       NA
alpha1     0.30258      0.04235    7.145 9.03e-13 ***
beta1      0.67077      0.02704   24.808  < 2e-16 ***
Standardised Residuals Tests:
Statistic p-Value
Jarque-Bera Test   R    Chi^2  630.635   0
Shapiro-Wilk Test  R    W      0.9645776 1.125997e-15
Ljung-Box Test     R    Q(10)  4.193607  0.9381906
Ljung-Box Test     R    Q(15)  16.91181  0.3241637
Ljung-Box Test     R    Q(20)  20.21807  0.4443647
Ljung-Box Test     R^2  Q(10)  6.568519  0.7654543
Ljung-Box Test     R^2  Q(15)  8.673675  0.8939526
Ljung-Box Test     R^2  Q(20)  9.695129  0.9733692
LM Arch Test       R    TR^2   6.634444  0.8807961
```

Table 3.13: Statistical equation of ARMA-GARCH model
(for the entire IEP time series).

	Statistical equation of ARMA-GARCH model	MSE
For Iranian electricity price time series	$r_t - r_{t-1} - 0.13309\ r_{t-2} - 0.1182\ r_{t-3} - 0.05846\ r_{t-4} - 0.18861\ r_{t-7} + 017889 \ = a_t - 0.23817$ $a_t = \sigma_t \varepsilon_t$ $\sigma^2 = 0.30258\ \varepsilon^2{}_{t-1} + 0.67077\ \sigma^2{}_{t-1}$	0.9970

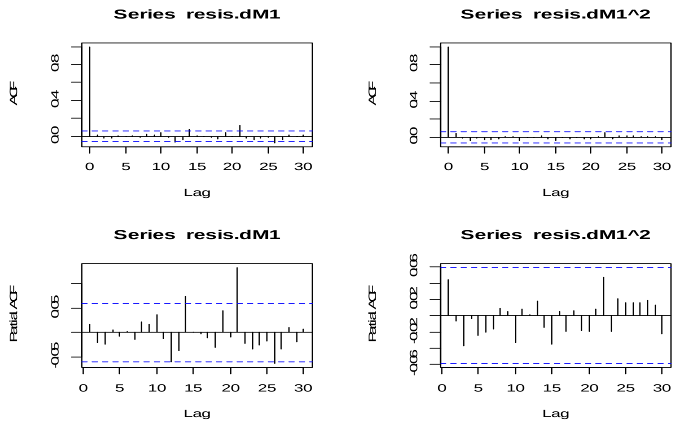


Figure 3.16: ACF and PACF of the (squared) residuals of the (IEP) ARIMA-GARCH model.

According to the ACF and PACF plots in Figure 3.16, the (squared) residual analysis displays no volatility clustering in the model. In contrast with this result, Figure 3.17 shows a big heavy tail in Q-Q plots. The histogram of residuals also proves that it is not a Gaussian distribution.

In Figure 3.18, there are some obvious serial correlations occurring in the residuals. Table 3.12 points to the unit roots in this model, because one of the coefficient related to the AR(1) section is equal to exactly one (Tsay, 2005; Box et al., 2013). As a result, this model may not be suitable or valid for estimating IEP behavior in this energy market.

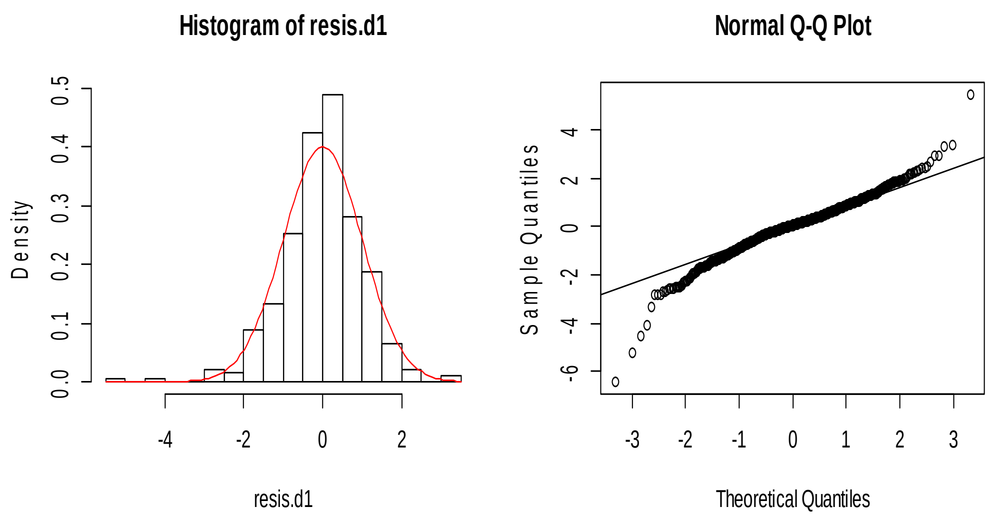


Figure 3.17: Q-Q plot and histogram of residuals in the ARIMA-GARCH model for the whole daily IEP price time series.

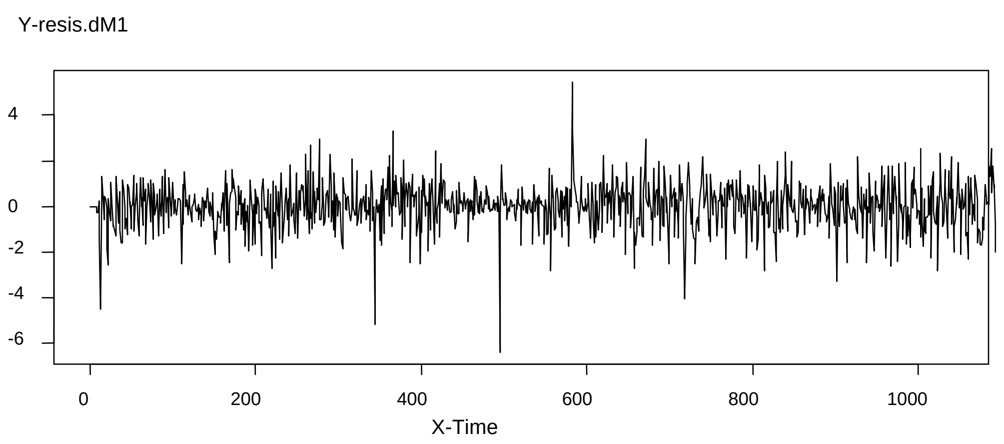


Figure 3.18: Behavior of residuals in the ARMA-GARCH model (IEP time series).

3.1.2.D ARMA-TGARCH model

As proven previously, the IEP has two breakpoints in its time series. The existence of these breakpoints will indeed influence the choice of time series model, as they indicate the thresholds in the thesis observations (Pfaff, 2008). Therefore, three separate parts have been observed in the treatment of the time series. This means the IEP time series also has different and unique (nonlinear) behavior in each section. These features point toward the application of ARMA-TGARCH models as a model that may cover all conditions existing in this time series (Narzo et al., 2008; Muñoz et al., 2007; Tsay, 2005; Wurtz et al., 2006; Zhang, 2009).

Therefore, the ARMA-TGARCH model has been derived for the IEP time series; see Table 3.14. To do so, each segment's behavior has to be modeled separately according to ARMA-GARCH. This means that the aggregation of all ARMA-GARCH models obtained for the three sections of the IEP time series have resulted in one ARMA-TGARCH model; see Table 3.15 (Muñoz et al., 2007; Wurtz et al., 2006; Zhang, 2009; Narzo et al., 2008; Tsay, 2005).

Furthermore, it is obvious that the residuals of each ARMA-GARCH model do not follow a Gaussian distribution. This is evident from the non-normal distributions of the residuals conducted using the Jarque-Bera and Shapiro-Wilk tests, which are employed to detect Gaussianity in distributions; see Table 3.15.

The Gaussianity Null Hypothesis in the Jarque-Bera Test (used for testing kurtosis and skewness of data that matches a Gaussian distribution) can be rejected, as the p-value is less than 0.05. The values obtained for kurtosis and skewness do not match normal distribution skewness, which is equal to 0 and kurtosis equals to 3.

The Q-Q plots and histogram of the residuals also prove this point clearly; these models do not exhibit any normal distributions—see Figure 3.19-all parts.

Here, in the ARMA-GARCH model related to second section of the times series, the conditional variance distribution follows a Skewed–Generalized Error Distribution; refer to Zhang, (2009).

The Shapiro-Wilk Test demonstrates this and the standardized residuals test proves the residuals in the time series do not follow any normally distributed population; see Table 3.15.

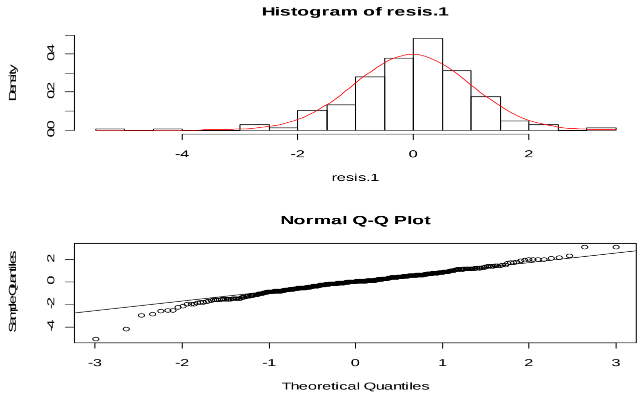
Table 3.14: Statistical equation of the ARMA-TGARCH model (for three parts of IEP time series).

	Statistical equation of ARMA-TGARCH Model	MSE
First ARMA-GARCH model	$r_t - 0.9873\ r_{t-1} = a_t - 0.25274\ a_{t-1}$ $a_t = \sigma_t \varepsilon_t$ $\sigma^2 = 0.026585 + 0.115902\ \varepsilon^2_{t-1} + 0.844564\ \sigma^2_{t-1}$	1.001675
Second ARMA GARCH model	$r_t - 0.885562\ r_{t-1} - 0.0653546\ r_{t-3} - 3.424097 = a_t - 0.416411\ a_{t-1}$ $a_t = \sigma_t \varepsilon_t$ $\sigma^2 = 0.028810 + 0.426834\ \varepsilon^2_{t-1} + 0.523748\ \sigma^2_{t-1}$	1.52092
Third ARMA GARCH model	$r_t - 0.638757 r_{t-1} + 0.288546 r_{t-2} + 0.465986 r_{t-3} - 0.121528\ r_{t-}$ $- 0.146785\ r_{t-7} + 0.122225\ r_{t-8} = a_t - 0.525785\ a_{t-2}$ $a_t = \sigma_t \varepsilon_t$ $\sigma^2 = 0.016495 + 0.155896\ \varepsilon^2_{t-1} + 0.851437\ \sigma^2_{t-1}$	0.9751998

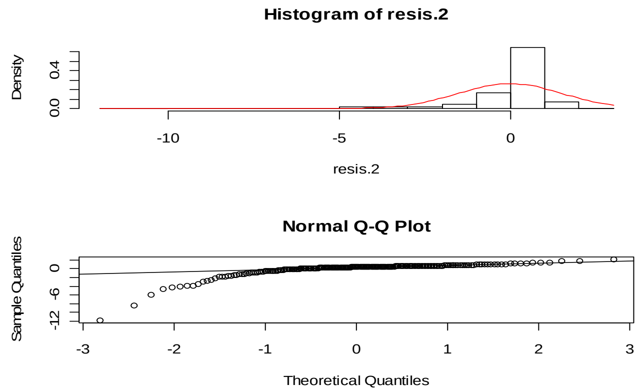
In Figure 3.20, the autocorrelation (ACF) and partial correlation (PACF) of the residuals further suggest that these may be appropriate models for the given data series; also see Figure 3.21.

Furthermore, the poly root function is applied to find the zeroes of the polynomials in the AR part of these three ARMA-GARCH models; see Table 3.16. The AR (p) process is stable if the roots of the lag polynomial lie outside the unit circle(see Stigler (2008)).

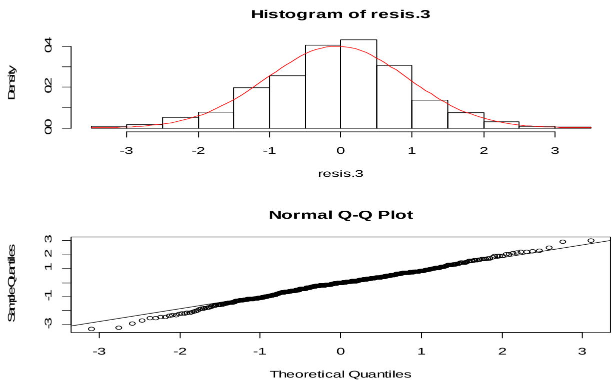
The results of this test indicate the existence of roots in the ARMA-TGARCH model. In other words, the characteristic polynomial has a unit root(see Pfaff, 2008; Box, et al., 2008; Prasolov, 2009). Hence, this result verifies that the developed models are invalid.



A-First ARMA-GARCH model.

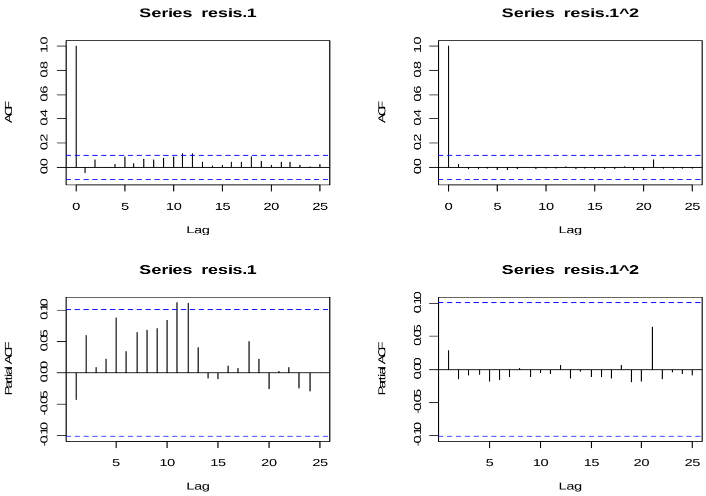


B-Second ARMA-GARCH model.

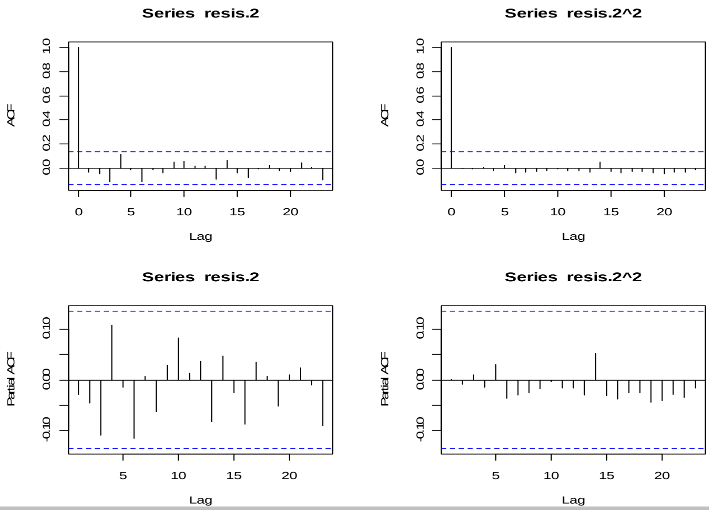


C-Third ARMA-GARCH model.

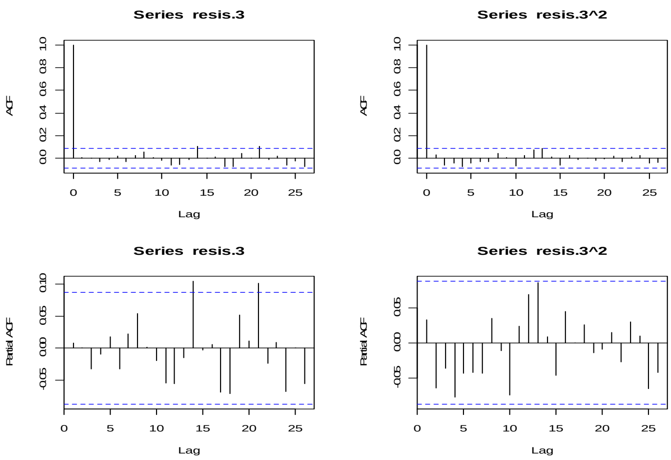
Figure 3.19: Histogram and Q-Q plots of the ARMA-TGARCH model (three parts of the IEP time series).



A- First ARMA-GARCH model.



B-Second ARMA-GARCH model.



C-Third ARMA-GARCH model.

Figure 3.20: ACF and PACF of the (regular and squared) residuals of the ARMA-TGARCH model (three parts of IEP time series).

Table 3.15: Estimated ARMA-TGARCH model for three parts of the IEP time series.

```
First part , norm Coefficient(s):
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.673994    0.464919    1.450 0.147141
ar1     0.987377    0.008814  112.024  < 2e-16 ***
ma1    -0.252745    0.059598   -4.241 2.23e-05 ***
omega   0.026585    0.007555    3.519 0.000434 ***
alpha1  0.115902    0.039147    2.961 0.003069 **
beta1   0.844564    0.034710   24.332  < 2e-16 ***
Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  97.883    0
 Shapiro-Wilk Test  R    W      0.973392  3.033061e-06
 Ljung-Box Test     R    Q(10)  17.64684  0.06122122
 Ljung-Box Test     R    Q(15)  24.63004  0.05513787
 Ljung-Box Test     R    Q(20)  29.47849  0.07875619
 Ljung-Box Test     R^2  Q(10)  6.543618  0.7677127
 Ljung-Box Test     R^2  Q(15)  8.776766  0.8888973
 Ljung-Box Test     R^2  Q(20)  13.40343  0.8594116
 LM Arch Test       R    TR^2   7.856052  0.7962758
```

R-code(8):

GARCH Modelling Call: garch1= garchFit(formula = ~arma(1, 1) + garch(1, 1), data = IEP.lin1, trace = F)

```
Second part , Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu      3.424097    0.022529  151.984  < 2e-16 ***
ar1     0.885562    0.011427   77.499  < 2e-16 ***
ar3     0.065354    0.014225    4.594 4.34e-06 ***
ma1    -0.416411    0.010548  -39.478  < 2e-16 ***
omega   0.028810    0.003223    8.940  < 2e-16 ***
alpha1  0.426838    0.032655   13.071  < 2e-16 ***
beta1   0.523748    0.020844   25.127  < 2e-16 ***
skew    0.681544    0.013918   48.968  < 2e-16 ***
shape   1.000000    0.056112   17.822  < 2e-16 ***
Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  2277.248  0
 Shapiro-Wilk Test  R    W      0.7679648 0
 Ljung-Box Test     R    Q(10)  6.065353  0.809743
 Ljung-Box Test     R    Q(15)  9.170979  0.868409
 Ljung-Box Test     R    Q(20)  11.51765  0.9316786
 Ljung-Box Test     R^2  Q(10)  1.039680  0.9997943
 Ljung-Box Test     R^2  Q(15)  1.427085  0.999997
 Ljung-Box Test     R^2  Q(20)  1.972447  1
 LM Arch Test       R    TR^2   1.432893  0.999898
```

R-CODE(9):

GARCH Modelling Call: Garch2=garchFit(formula = ~arma(3, 1) + garch(1, 1), data = IEP.lin2, cond.dist = "sged", trace = F)

```
Third part , Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu      3.268452    1.949372    1.677 0.093607 .
ar1     0.638757    0.162484    3.931 8.45e-05 ***
ar2    -0.288546    0.158237   -1.824 0.068228 .
ar3     0.465986    0.138235    3.371 0.000749 ***
ar4     0.121528    0.061250    1.984 0.047239 *
ar5    -0.019616    0.062197   -0.315 0.752474
ar6     0.024550    0.062861    0.391 0.696134
ar7     0.146785    0.062203    2.360 0.018286 *
ar8    -0.122225    0.038981   -3.135 0.001716 **
ma1     0.188779    0.169777    1.112 0.266171
ma2     0.525785    0.145561    3.612 0.000304 ***
omega   0.016495    0.007597    2.171 0.029913 *
alpha1  0.155896    0.042815    3.641 0.000271 ***
beta1   0.851437    0.029851   28.523  < 2e-16 ***
shape   7.164166    2.746528    2.608 0.009095 **
Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  29.62067  3.697883e-07
 Shapiro-Wilk Test  R    W      0.987956  0.0003852421
 Ljung-Box Test     R    Q(10)  3.199486  0.9763319
 Ljung-Box Test     R    Q(15)  12.32497  0.6542833
 Ljung-Box Test     R    Q(20)  18.79374  0.5352675
 Ljung-Box Test     R^2  Q(10)  11.83623  0.2961663
 Ljung-Box Test     R^2  Q(15)  21.42600  0.1237616
 Ljung-Box Test     R^2  Q(20)  21.98355  0.3414037
 LM Arch Test       R    TR^2   16.64297  0.1635281
```

R-Code(10):

GARCH Modelling call: garchFit(formula = ~arma(8, 2) + garch(1, 1), data = IEP.lin3, cond.dist = "std", trace = F)

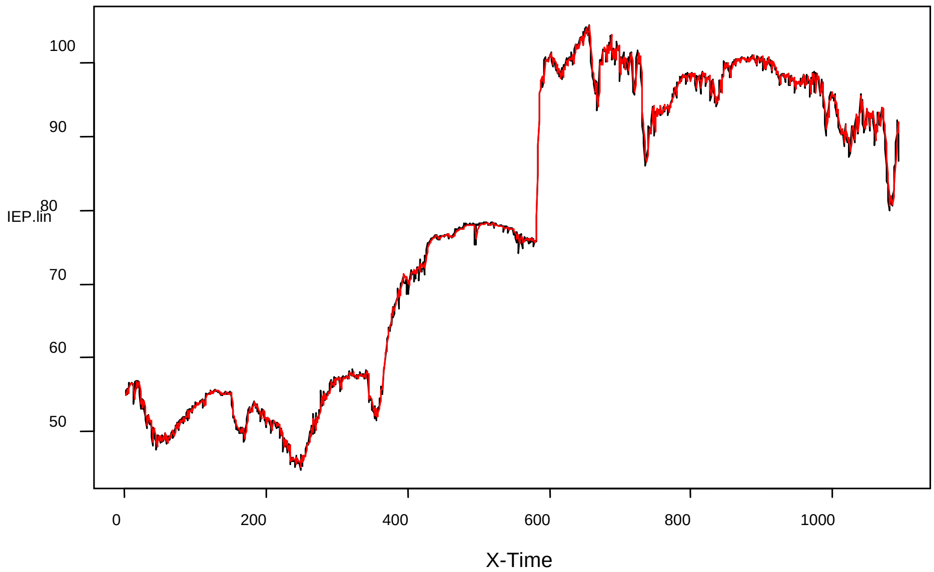


Figure 3.21: Overlapping the experience data on the ARMA-TGARCH model.

Table 3.16: Stationary univariate analysis of ARMA-TGARCH models.

R Code(11): Mod(polyroots(1,φ_i))	The poly roots for AR(p) polynomial in our ARMA-GARCH Model
ARMA-GARCH models of Iranian electricity price time series-first Section.	To estimate the roots of AR(1)-Process with φ_1= 0.987377: 1.012784
Iranian electricity price time series–second section.	To estimate the roots of AR(3)-Process with φ_1= 0.885562, φ_3= -0.065354: 1.045007, 3.826522
Iranian electricity price time series –third section.	To estimate the roots of AR(8)-Process with φ_1= 0.638757, φ_1= - 0.288546, φ_1= 0.465986, φ_1= 0.121528, φ_1= - 0.019616, φ_1= 0.024550, φ_1= 0.146785, φ_1= - 0.122225: 1.385537 ,1.116540, 1.116540 ,1.015829 ,1.390969, 1.390969, 1.385537 ,1.739399

BFAST methodology is often used as a tool to detect generic changes in time series (Verbesselt et al., 2010) involving the identification and characterization of breaks for additional seasonal *algorithms and trends.* This detection analysis is basically formed according to a decomposition model, which assumes three component behaviors exist in the time series. "An additive decomposition model is used to iteratively fit a piecewise linear trend and a seasonal model" (Verbesselt et al., 2010). The general model is given by Eq. (3.9), where Y_t is the observed data at time t=1, 2,.., n=1095.; T_t is the trend component; S_t is the seasonal component; and e_t is random noise.

$$\mathbf{Y_t = T_t + s_t + e_t}$$

Eq. 3.9

The BFAST integrates the iterative decomposition of time series into two trends: seasonal and noise components, with methods for detecting changes within time series. These methods are not specific to any particular data type and can be applied to time series without having to normalize for land cover types, select a reference period, or change trajectory (or specific thresholds), as noted by Verbesselt et al. (2010).

Therefore, nine break points are found at all three confidence interval levels (90%, 99%, and 95%) in the IEP time series in Table 3.17. Here, all three break points are detected at a 95% confidence interval in the IEP time series. These occur on the 366th day, the 585th day and the 846th day of this time series, and are indicated on the left-hand side of Figure 3.22 as "Hidden Lines". The existence of these breakpoints will surely influence the choice of the time series model, as they indicate thresholds in the observations (Pfaff, 2008).

Hence, four separate parts can be noted in the treatment of the time series, which are as follows:

a) March 21, 2007 to March 19, 2008 (approximately one full year)
b) March 20, 2008 to November 25, 2008 (four months prior to the Iranian New Year)
c) November 26, 2008 to July 13, 2009
d) July 14, 2009 to March 20, 2010.

On the other hand, some kind of volatility is observed even after detrending the residuals of the BFAST model in Figure 3.23-A. Volatility has a great deal of influence on the time series modelling; see Figure 3.23-B. Therefore, in considering these conditions—the volatility and the three exciting breakpoints in the structure of the time series—a new estimated ARMA-TGARCH model will be proposed in order to make the relevant comparisons with the results of the previous models.

Table 3.17: Trend detecting with BFAST methods.

```
R-code(12): iran.none=bfast(iran.ts,h=0.2,max.iter=10,season="none")
TREND BREAKPOINTS - Confidence intervals for breakpoints of IEP time series:
Call: confint.breakpointsfull(object = bp.Vt, het.err = FALSE)
                    Breakpoints at observation number
  2.5 % breakpoints 97.5 %
1   365           366     368
2   584           585     586
3   839           846     847
                    Corresponding to breakdates
  2.5 %   breakpoints 97.5 %
1 53(1)   53(2)       53(4)
2 84(3)   84(4)       84(5)
3 120(6)  121(6)      121(7)
SEASONAL BREAKPOINTS:   None
```

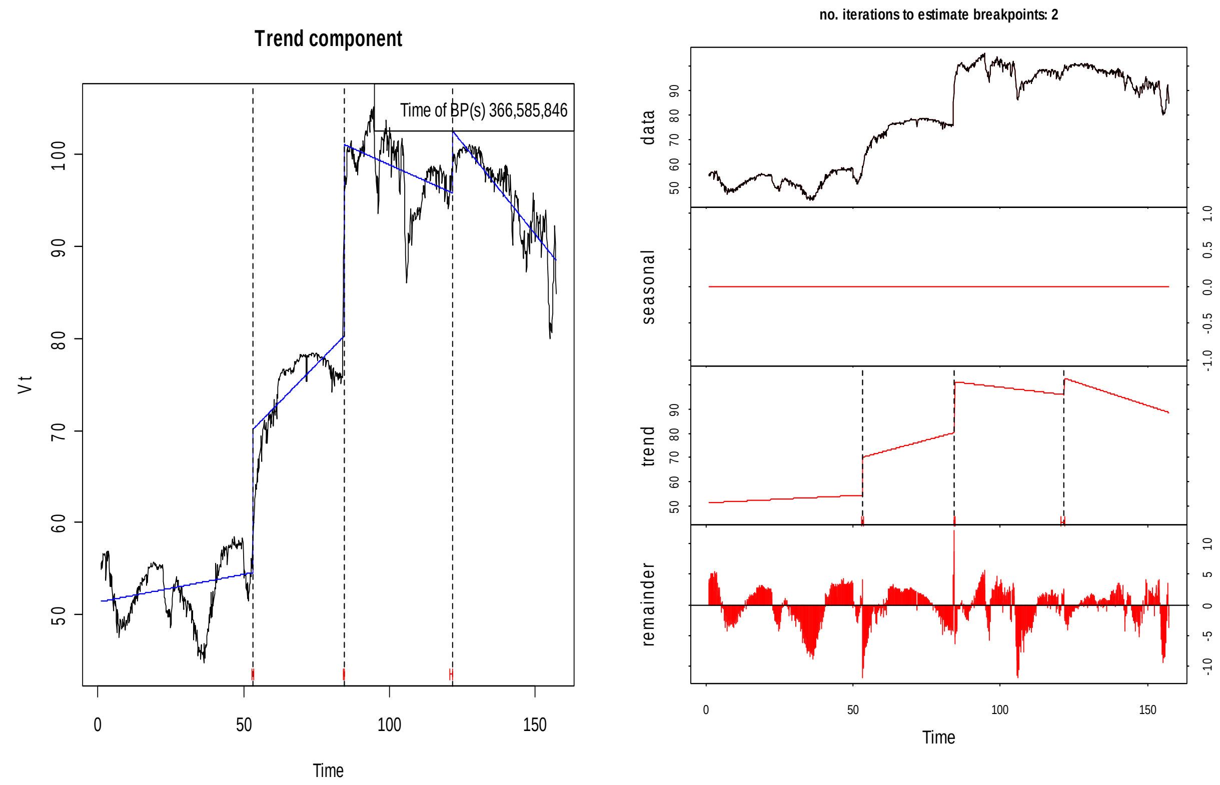
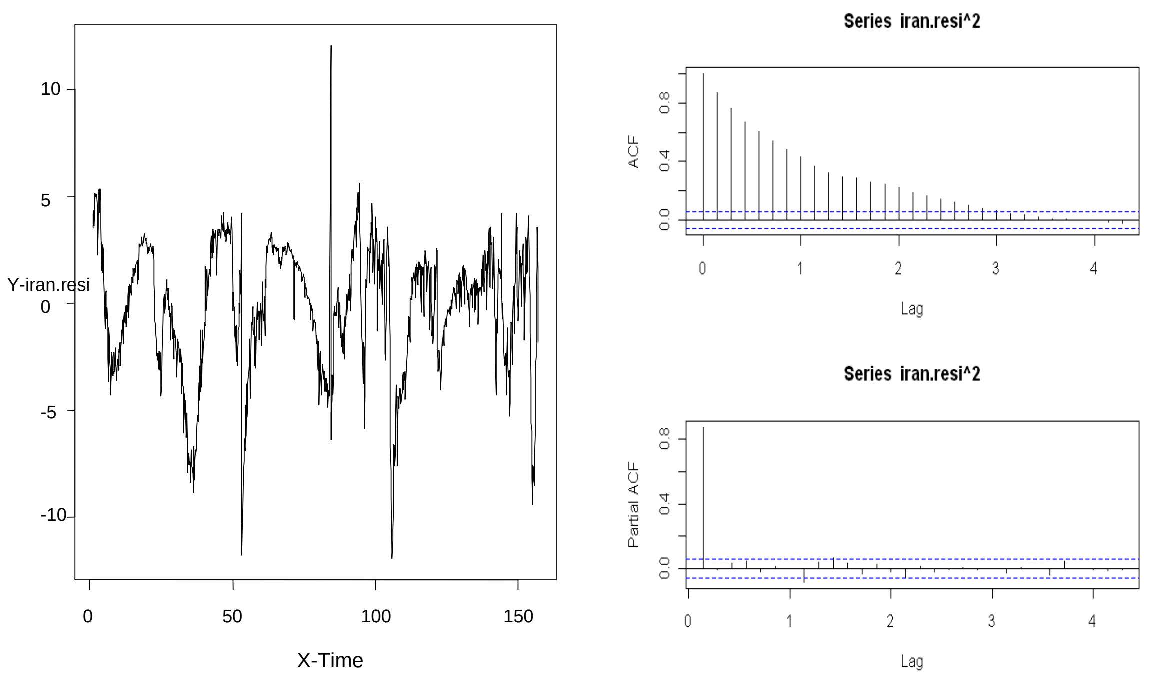


Figure 3.22: Plot of BFAST trend detecting by breakpoints.

3.1.2.E ARMA-TGARCH Models after detrending

In the explanation of the previous ARMA-TGARCH model, unit roots were observed in the ARMA-GARCH models related to first and second parts of the IEP time series. After detrending the time series using the BFAST model, some serial correlations in the residuals were discovered, as seen in Figure 3.23. The result once again points to making estimates with the ARMA-GARCH model in each part of the IEP; see Figure 3.22.

The statistical equation used in ARMA-TGARCH models is depicted in Table 3.18. Here, there are four separate estimated ARMA-GARCH models for the IEP time series, employing the breakpoints obtained from the BFAST model in previous section; see Table 3.19 (Verbesselt et al., 2010).



(A)- Detrended the IEP time series.	(B)- The residuals analysis from the BFAST.

Figure 3.23: (A)- Detrended IEP time series using BFAST. (B)- Residuals analysis of the BFAST.

Table 3.18: Statistical equation of four ARMA-GARCH models (after detrending).

	Statistical equation of ARMA-TGARCH Model	MSE
A-First ARMA-GARCH model	$r_t = a_t - 0.2641948a_{t-1}$ $a_t = \sigma_t \varepsilon_t$ $\sigma^2 = 0.029284 + 0.1203102\varepsilon^2{}_{t-1} + 0.8361440\sigma^2{}_{t-1}$	1.001776
B-Second ARMA-GARCH model	$r_t = a_t - 0.28762\, a_{t-1}$ $a_t = \sigma_t \varepsilon_t$ $\sigma^2_{t-1} = 0.08819 + 0.45640\, \varepsilon^2{}_{t-1} + 0.54072\, \sigma^2_{t-1}$	1.004753
C- Third ARMA-GARCH model	$r_t - 0.6563\, r_{t-1} = a_t - 0.76807\, a_{t-1}$ $a_t = \sigma_t \varepsilon_t$ $\sigma^2_{t-1} = 0.12611\, \varepsilon^2{}_{t-1} + 0.83328\, \sigma^2_{t-1}$	0.992377
D-Four ARMA-GARCH model	$r_t = a_t - 0.3599973\, a_{t-1} + 0.1558994\, a_{t-14}$ $a_t = \sigma_t \varepsilon_t$ $\sigma^2_{t-1} = 0.7138358\, \sigma^2_{t-1}$	0.9166025

Here, the residuals of all four ARMA-GARCH models do not follow a Gaussian distribution. The Q-Q plots and histogram of the residuals clearly exhibit the fact that these models do not show any normal distributions; see Figure 3.24. Despite this, the

ACF and PACF of the (squared) residuals in Figure 3.25 further suggest that these models can be a good possibility for all four parts of the IEP time series.

The poly roots test describes that in this ARMA-TGARCH model, there are no unit roots in the AR section of the model shown in Table 3.19, because the coefficient is greater than one, (refer to Pfaff, 2008; Box et al., 2013; Prasolov, 2009). All the results indicate that this can be a suitable model for estimating the behavior of prices in the Iranian electricity market.

Table 3.19: Estimated ARMA-TGARCH models (for four parts of the IEP time series). after detecting breakpoints and detrending

```
R-code(13):
iran.d1=garchFit(formula=~arma(0,1)+garch(1,1),data=iran.pr.d1)
```

```
First section
Coefficient(s)
         Estimate      Std. Error   t-value   Pr(>|t|)
mu      0.0002496(μ)    0.0263830    0.009     0.99245
ma1    -0.2641948(θ1)  0.0591939   -4.463     8.07e-06 ***
omega   0.0292842(α0)  0.0147700    1.983     0.04740 *
alpha1  0.1203102(α)    0.0434775    2.767     0.00565 **
beta1   0.8361440(β)    0.0501306    16.679   < 2e-16 ***
```

```
R-code(14):
iran.d2=garchFit(formula=~arma(0,1)+garch(1,1),data=iran.pr.d2)
```

```
Second section
Coefficient(s)
        Estimate      Std. Error  t-value Pr(>|t|)
mu       0.01224(μ)     0.02850    0.430   0.667452
ma1     -0.28762(θ1)   0.08385   -3.430   0.000603 ***
omega    0.08819(α0)   0.02473    3.566   0.000363 ***
alpha1   0.45640(α)     0.11542    3.954   7.68e-05 ***
beta1    0.54072(β)     0.07835    6.901   5.16e-12 ***
```

```
R-code(15):
iran.d3=garchFit(formula=~arma(1,1)+garch(1,1),data=iran.pr.d3,cond.dist ="std" )
```

```
Third section
Error Analysis:
        Estimate       Std. Error   t value   Pr(>|t|)
mu       0.01956 (μ)    0.01938     1.010     0.313
ar1      0.65636 (φ1)   0.16649     3.942     8.07e-05 ***
ma1     -0.76807 (θ1)   0.16109    -4.768     1.86e-06 ***
omega    0.05518 (α0)   0.04181     1.320     0.187
alpha1   0.12611 (α)     0.06110     2.064     0.039 *
beta1    0.83328 (β)     0.07701     10.820   < 2e-16 ***
shape   10.00000         6.89342     1.451     0.147
```

```
R-code(16):
garchFit(formula = ~arma(0, 14) + garch(1, 2), data = iran.pr.d4,cond.dist = "norm")
```

```
Fourth Section
ARMA-GARCHmodel-Error Analysis:
        Estimate       Std. Error    t value  Pr(>|t|)
mu      -0.05686 (μ)      0.03130    -1.816    0.069297 .
ma1**   -0.30447 (φ1)     0.08385    -3.631    0.000282 ***
omega    0.01482 (α0)     0.01515     0.979    0.327751
alpha1   0.27724 (α1)     0.08081     3.431    0.000602 ***
beta1    0.10734 (β1)     0.13575     0.791    0.429106
beta2    0.64223 (β2)     0.14399     4.460    8.19e-06 ***
```

Table 3.20: Stationary univariate analysis for four estimated ARMA-GARCH models.

R Code(17): Mod(polyroots(1,φ_i))	The poly roots of AR(p) polynomial in ARMA-TGARCH Model
Second part of IEP model	Estimation of AR(1)-Process with φ_1=0.6563: 1.766784

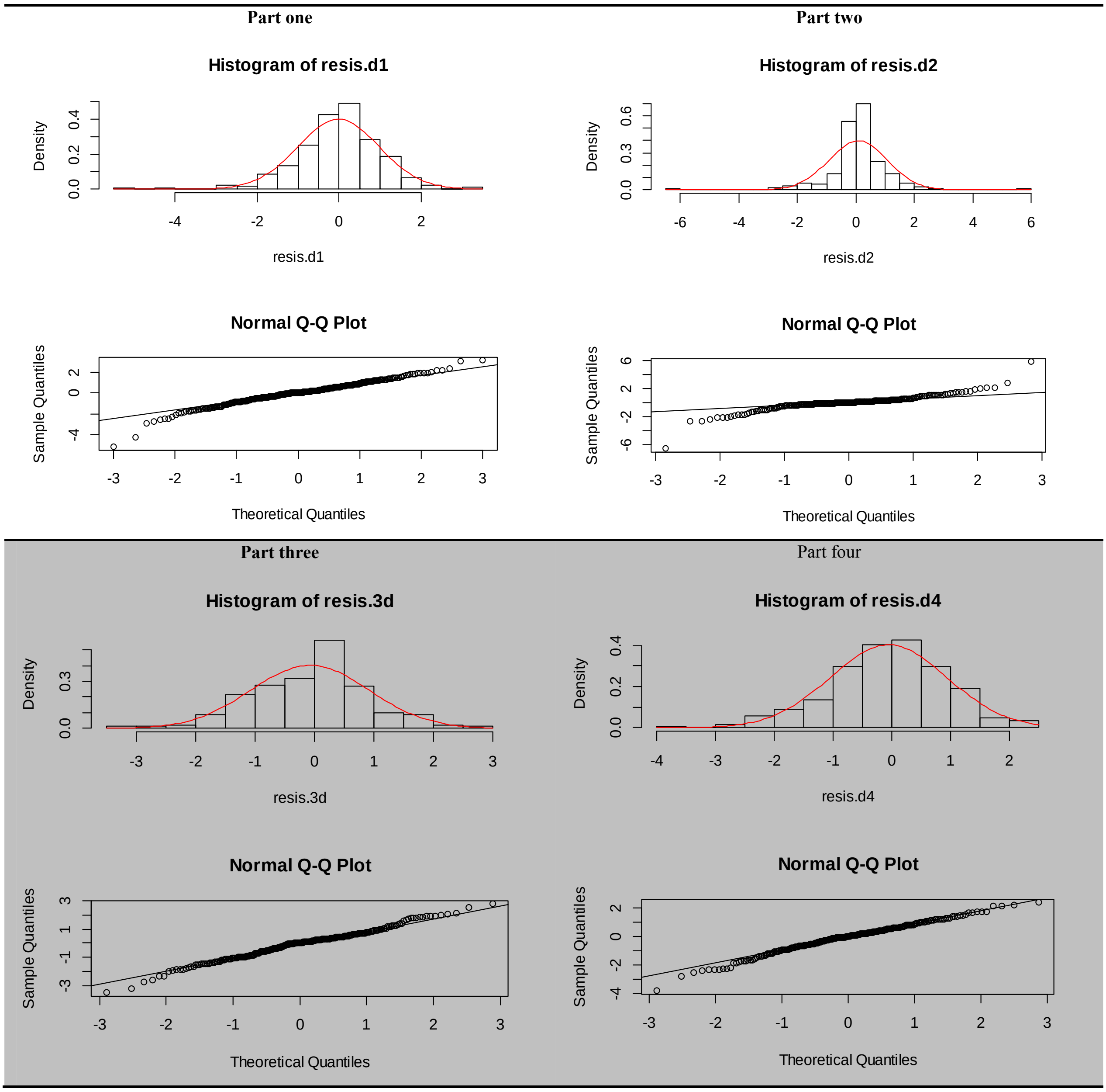


Figure 3.24: Histogram and Q-Q plot from the ARMA-TGARCH model
(for four parts of the IEP time series).

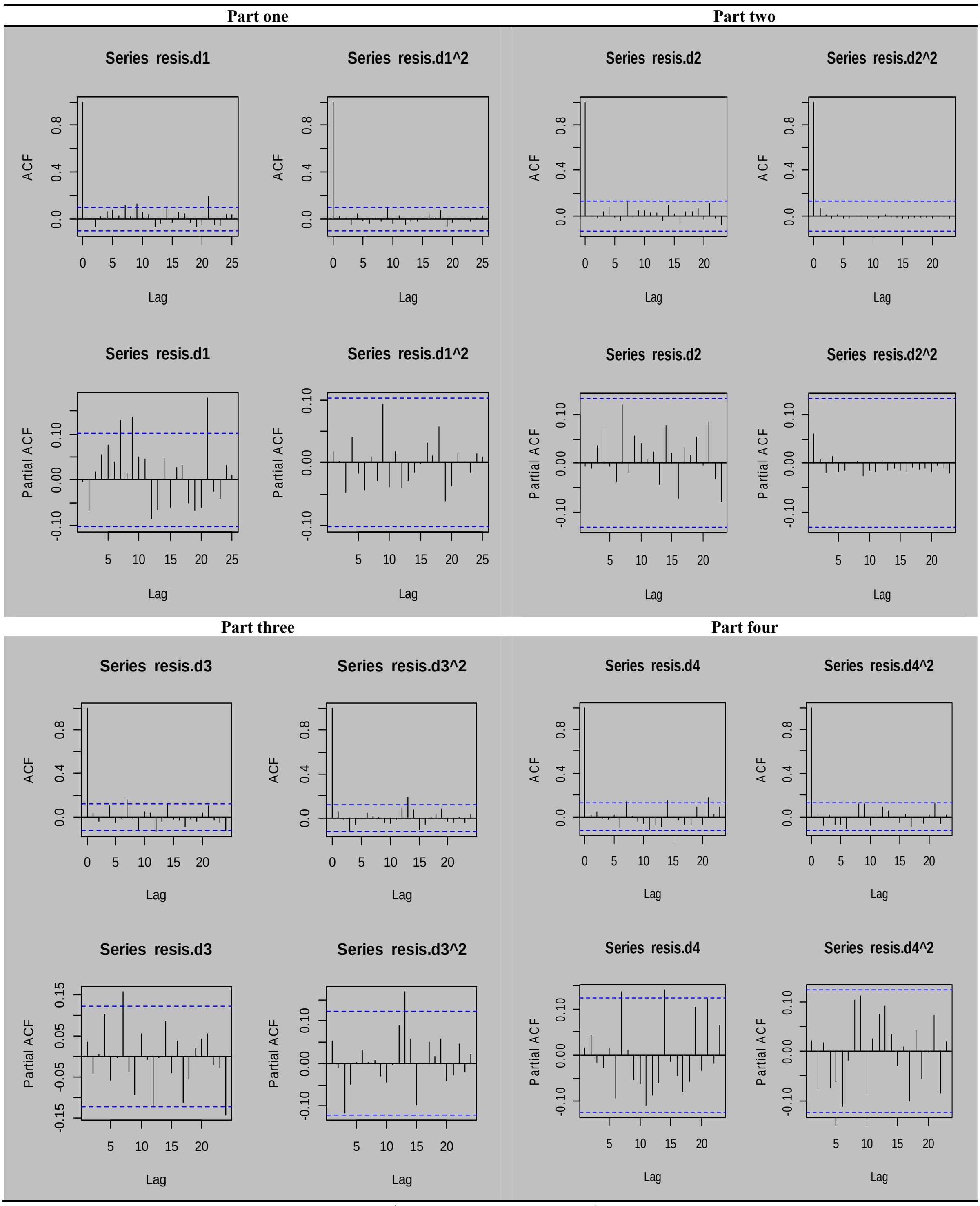


Figure 3.25: ACF and PACF of the (regular and squared) residuals ARMA-TGARCH model (for four parts of the IEP time series).

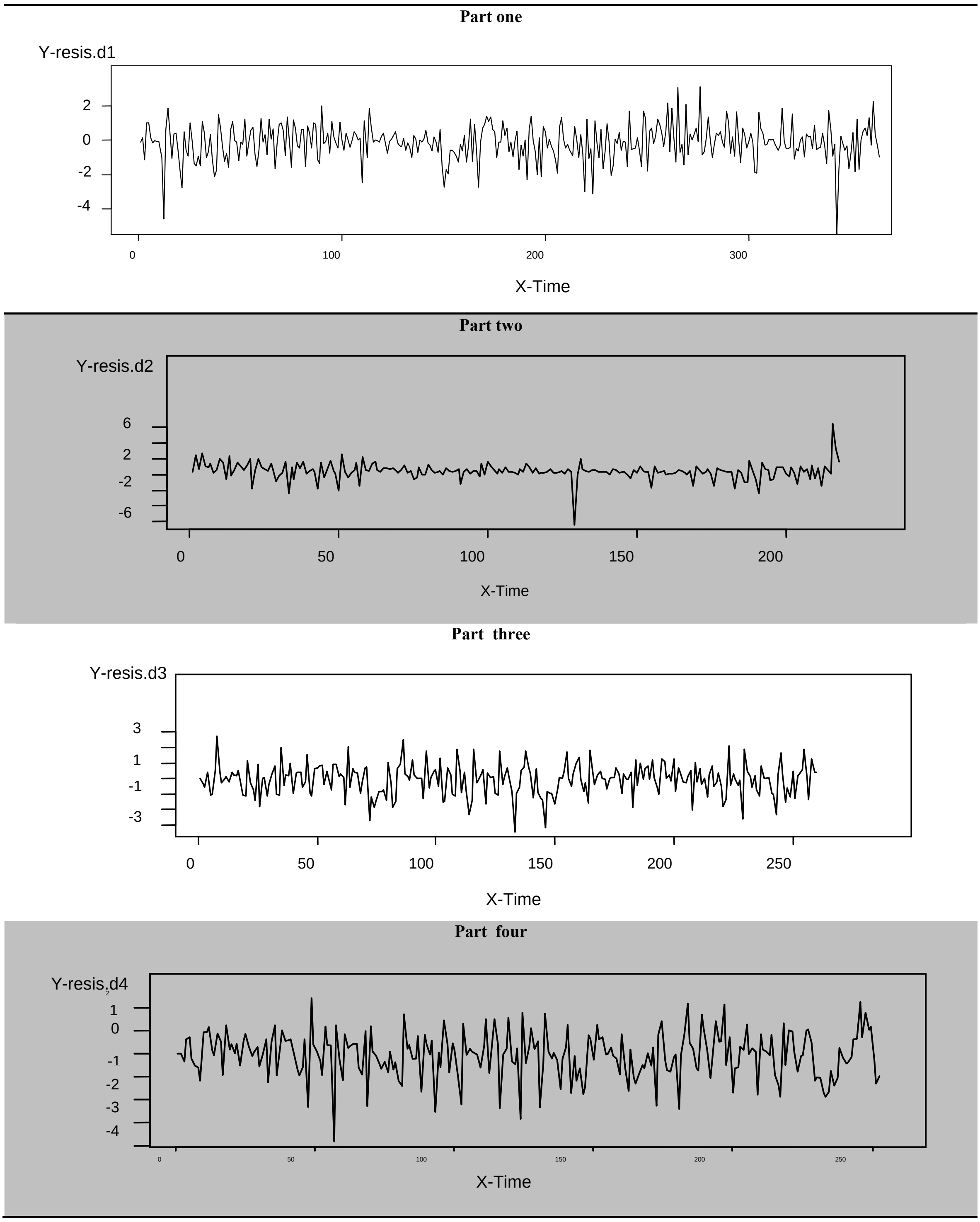


Figure 3.26: The behavior of residuals in the ARMA-TGARCH model (for four parts of the IEP time series).

3.1.2.F APARCH model

After an initial study into the APARCH model, a particular type of ARCH model (Ding, 2011), it was decided that another suitable and validation model had been found.
The Asymmetric Power ARCH model (APARCH) devised by Ding et al. (1993) is one of the most promising ARCH type models. This model expresses the fat tails, excess kurtosis and leverage effects very well. The general structure is as follows:

$y_t = x_t\xi + \varepsilon_t$ t=1,2…,T.
$a_t = \sigma_t\varepsilon_t$

$$\boldsymbol{\sigma_t^\delta = \alpha_0 + \sum_{i=1}^{m} \alpha_i (|(a_{t-i} - \gamma_i a_{t-i})^\delta| + \sum_{j=1}^{s} \beta_i B_{t-1}^\delta}$$ Eq. 3.10

This mean equation y_t=x_t ξ+ε_t could also be written as:

$$y_t = E(y_t|\psi_{t-1}) + a_t$$

where E (yt|ψt−1) is the conditional mean of yt, given ψt−1. ψt−1 is the whole information at time t-1.
$\psi_t=\{y_t,y_{t-1},\dots,y_1,y_0,x_t,x_{t-1},\dots,x_1,x_0\}$

where ξ, ω, αj, γj, βi and δ are the parameters which are needed to be estimated. γj, reflects the leverage effect. Then, εt is given at the normal distribution, εt ~N (0, 1). The δ is a non-negative real number. In particular δ = 2 gives rise to the GARCH model and δ = 0 corresponds to using log (σ_t).

$$a_t = \sigma_t\varepsilon_t$$
$$\sigma_t^\delta = \alpha_0 + \sum_{i=1}^{m} \alpha_i (|(a_{t-i} - \gamma_i a_{t-i})^\delta| + \sum_{j=1}^{s} \beta_i B_{t-1}^\delta$$
Eq. 3.11

Here, delta is equal to 0.748 and it would be like to estimate the parameters for these two models. A positive γ_j (gamma1) means that negative information and has stronger impact than the positive information on the price volatility. The quantity δ represents the leverage effect(Ding 2011). As result we have got at Table 3.21:

Table 3.21: Estimated APARCH model using the detrended daily IEP time series.

```
R-Code(18):
garchFit(~arma(1,2)+aparch(1,1),data=iran.resi,trace=F,cond.dist="sstd")
summary(iran.arma12.aparch11
```

```
Estimate   Std. Error  t value Pr(>|t|)
mu      -0.001929    0.012592   -0.153 0.878225
ar1      0.980806    0.004674  209.854  < 2e-16 ***
ma1     -0.191995    0.025254   -7.603 2.91e-14 ***
ma2     -0.059419    0.015698   -3.785 0.000154 ***
omega    0.039695    0.017237    2.303 0.021283 *
alpha1   0.285153    0.053255    5.354 8.58e-08 ***
gamma1   0.373741    0.095035    3.933 8.40e-05 ***
beta1    0.777590    0.038598   20.146  < 2e-16 ***
delta    0.748824    0.124645    6.008 1.88e-09 ***
skew     0.876720    0.032999   26.568  < 2e-16 ***
shape    3.352473    0.379126    8.843  < 2e-16 ***
```

Here, delta is equal and it would be like estimating the parameters of these two models. A positive γ_j means negative information has a stronger impact than positive information in terms of price volatility. The quantity of δ represents the leverage effect (Ding 2011). The results are shown in Table 3.21:

A-Histogram of the residuals. **B- Q-Q plot of the residuals.**

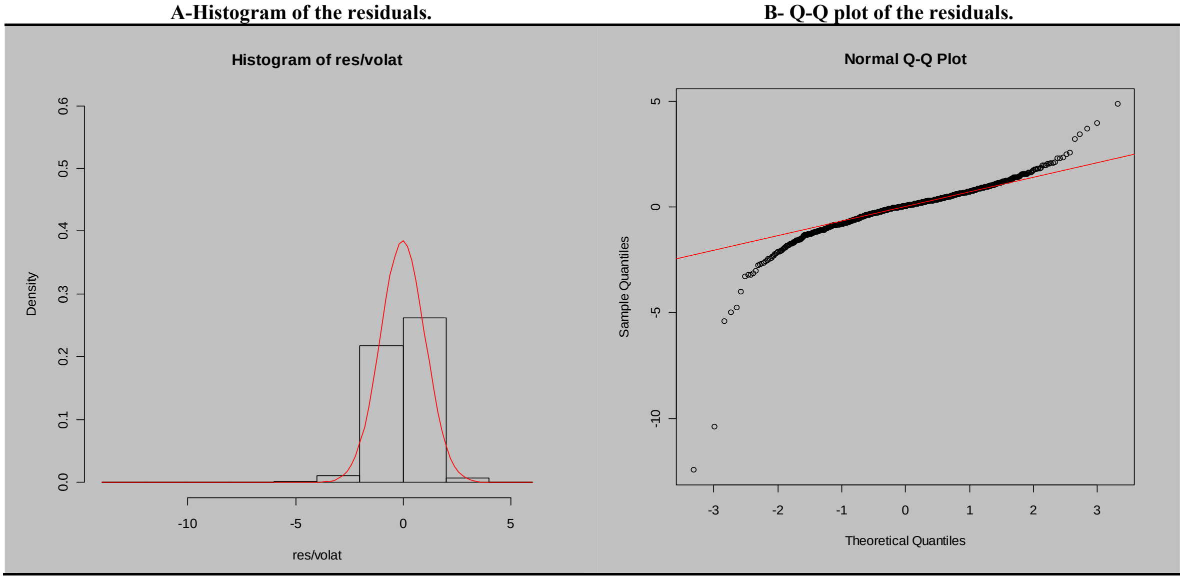


Figure 3.27: Residual analysis of APARCH model via the histogram and Q-Q plot.

The results obtained through the analysis of using this model are presented in Figure 3.27, which clearly demonstrates that this is a valid model, since there is neither autocorrelation nor volatility clustering in the residual, not to mention the fact that the heavy tail is truly small. All the estimations are significant, and the model-checking indicates that the model is suitable although the Normal Q-Q plot of the residuals exhibit heavy tails. The model equations are given as:

Table 3.22: Statistical equation of the APARCH model for the IEP time series.

Model	APARCH model-After detrending	MSE
for Iranian electricity price time series	$r^t - 0.980806r_{t-1} + 0.001929 = a_t - 0.191995a_{t-1} - 0.059419a_{t-2}$ $a_t = \sigma_t \varepsilon_t$ $\sigma_t^{0.75} = 0.039695 + \sum_{i=1}^{m} 0.285153(\|(a_{t-i}$ -0.373741$)^{0.75}$ $\| + \sum_{j=1}^{s} 0.777590\, B_{t-1}^{0.75}$	1.474514

3.1.3 Results

3.1.3.A Comparison of the Iranian electricity price time series models

The previous section discussed the model estimation approach for the IEP time series. As shown in Table 3.23, due to the volatility clustering of the residuals, the classic ARIMA models did not perform well and could not be utilized in estimating the IEP time series. The results of the Mean Square Error (MSE) Test(see Wu-Shyong and William,1994) in two SETAR models, i.e. the two and three regimes, suggests that three regimes may be a more suitable function for estimating IEP behavior pattern, as proven in this research. However, the validation of the SETAR models, because of the serial correlation amongst their residuals and existence of Unit Roots, is notably decreased. This also occurs in the APARCH model because of it residuals analysis; the volatility and heavy tail make this an unsuitable model for the IEP time series.

All of these results have led the researcher to the issue that prices in this market do not have any linear behavior and the patterns of the IEP time series is clearly nonlinear. On the other hand, a suitable ARMA-GARCH model cannot be found to estimate the serial dependence of the variance in the time series either, due to the nonlinear behavior of the IEP time series. Therefore, the ARMA-TGARCH model has been suggested for making the best possible estimation of the IEP time series.

In each part of this time series, the MSE related to the ARMA-GARCH model was found to be very low, much like the average values in the ARMA-TGARCH model. In addition, there is no serial correlation among the residuals computed for this model or for the ARMA-GARCH models related to each section. These results are similar to those found in other estimated ARMA-GARCH models. Therefore, all this suggests that the best model for predicting and describing the behavior of the IEP time series is the ARMA-TGARCH model.

This model, which was evaluated using three breakpoints, seems to be one of the best models for predicting the behavior of the IEP. The average MSEs in the ARMA-TGARCH model, aggregated from the three ARMA-GARCH models in Table 3.14, is greater than other one, aggregated from the four ARMA-GARCH models in Table 3.18.

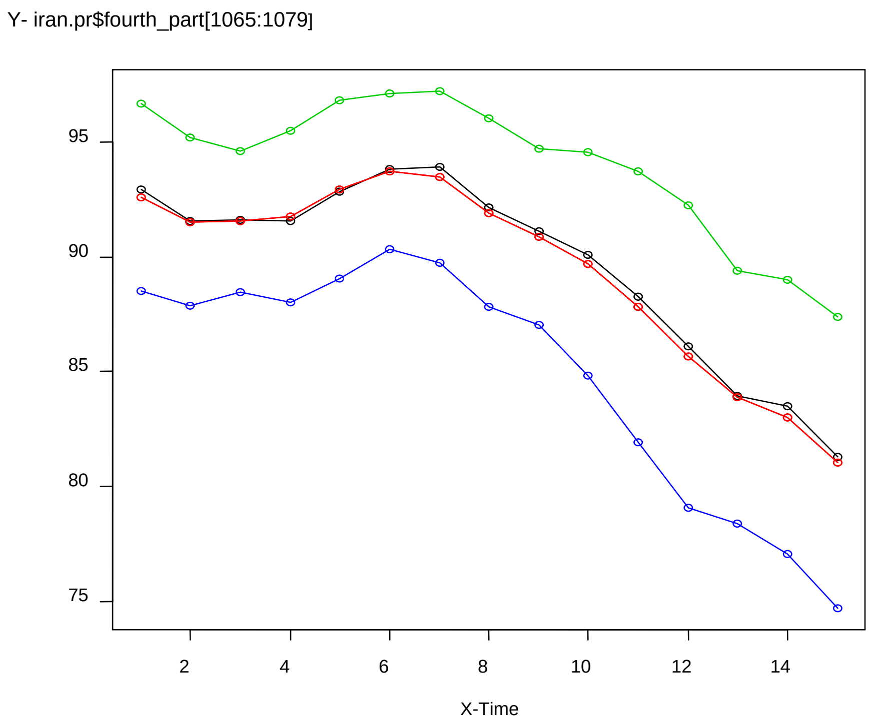
Table 3.23: Comparison of the estimated models for the IEP time series.

IEP time series model	Model validation	Residuals validation	No.Obs	MSE
ARIMA-365	No valid	volatility	365	0.5509449
ARIMA-581	No valid	volatility	216	0.505876
ARIMA-1095	No valid	volatility	514	1.315861
ARMA-GARCH –total data	No Valid	Volatility-Unitroots	1095	0.9970633
SETAR-Two regimes	Not accept	Not accept	1095	0.8613197
SETAR-Three regimes	Low Valid	Unitroots	1095	0.9118837
ARMA-TGARCH model –with two break points				
ARMA-GARCH (first part -365)	valid		365	1.001675
ARMA-GARCH (second part-581)	Low valid	Heavy tail	216	1.52092
ARMA-GARCH (third part-1081)	valid		514	0.9751998
Avarage of MSE for three ARMA-GARCH model	-	-	1095	1.1659299
ARMA-TGARCH model –with three break points				
ARMA-GARCH (first part -366)	valid	-	366	1.001776
ARMA-GARCH (second part-585)	valid	-	219	1.004753
ARMA-GARCH (third part-846)	valid	-	261	0.992377
ARMA-GARCH (fourth part-1081)	valid	-	249	0.9166025
Average of MSE for four ARMA-GARCH model after Detrended	-	-	1095	0.978877
APARCH after Detrended	Low valid	Heavy tail	1095	1.474514

3.1.3.B Prediction in sample of the Iranian electricity price time series

For the IEP, a prediction in sample can be made using the fourth part of the ARMA-TGARCH model in Table 3.18-D. The thesis has taken into consideration a daily forecast of the IEP over 14 days. This prediction was performed on from 1065th to 1079th day in the sample. As seen in Figure 3.28, the forecast is observed to be within the confidence intervals at the 95th percentile. The sample forecast has very similar behavior to the real data, therefore confirming that this model can be introduced as the most suitable model in our research.

In Chapter Four of this thesis, an out-of-sample prediction is provided via the simulation for the ARMA-TGARCH model, aggregated with four separate ARMA-GARCH models. For more detailed information, see Chapter Four.



Note: **Red points and lines** indicate forecasting. **Black points and lines** indicate the real price. **Green and blue points and lines** indicate confidence intervals.

Figure 3.28: IEP in-sample price forecasting over 14 days (1065th to 1079th) using the ARMA-TGARCH model (from its fourth section).

3.2 Time series analysis of Iranian electricity loads

This section has the same format as the previous section. Firstly, there is a data description of the Iranian electricity load (IEL) time series. Then, the time series analysis modelling is represented. A comparison of the models will be made in order to select the best model for IEL time series.

3.2.1 Data description of daily Iranian electricity loads

As explained in Chapter Two, load plays a crucial role in electricity markets, especially competitive ones. The significance of this index—as demand—in the electricity market also suggests the monitoring of the behavior of the daily IEL time series over the course of three years, so that the corresponding market responses could be tracked. The data was calculated on a daily basis, similarly to the daily IEP time series. The data reports began on March 21, 2007 (corresponding to the beginning of the Iranian New Year of 1386) and ended on March 20, 2010 (corresponding to the end of the Iranian year of 1388). The daily electricity load time series was calculated according to the amount of "hourly load" based on "kWh" that was reported by Ministry of Energy of the Islamic Republic of Iran (2010). Consequently, the valid load displays an indication of its total behavior during a 24-hour period. Here, these load time series are divided by 1000 to make the scale smaller and simplify the calculations. The total number of samples in the IEL time series is equal to 1095. Similar to the previous sections, "R" programming software was utilized as the statistical analysis tool (R Development Core Team, 2011a). Prior observations suggested that it would not be necessary to make use of a logarithmic transformation function, due to the approximately constant variance (Muñoz and Dickey, 2009). Figure 3.29 demonstrates the IEL time series during this period.

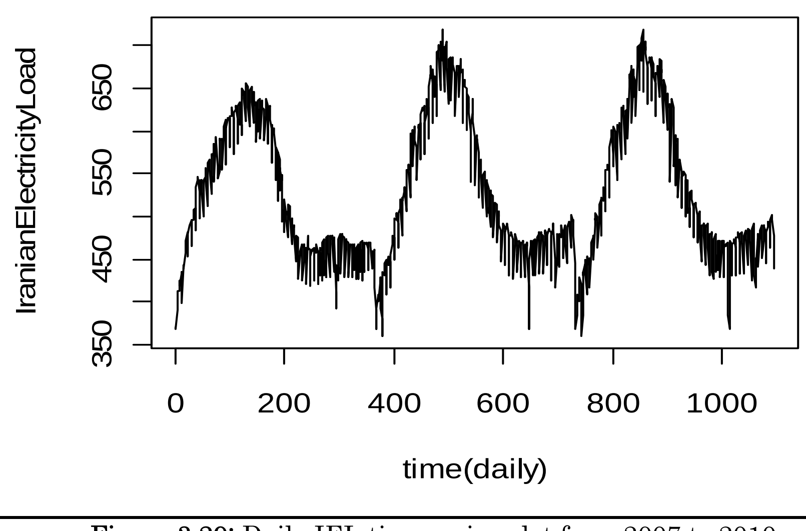


Figure 3.29: Daily IEL time series plot from 2007 to 2010.

This IEL plot exhibits an upward and downward trend in its daily values during the three sampled years. Initially, there are some spikes occurring on special dates, but these are not very high. Such variations clearly suggest that the IEL does not exhibit any stationary patterns in the time series (in order to simplify the evaluation, the observation values were divided by 1000).

Moreover, statistical tests, such as the" Jarque-Bera Test", have proven that the IEL time series does not have a Gaussian distribution, as seen in Table 3.24. Here, the p-value in the skewness test is greater than 0.05. However, Figure 3.30 shows that this result is not related to the histogram and there is no independent identification distribution, which sometimes occurs because of highly conflictive behavior that has been observed. The p-value of the "Jarque - Bera Normality Test" is also less than 0.05, evidence that skewness and kurtosis do not match a normal distribution. Based on the kurtosis (a null hypothesis is kurotsis=3), the p-value of this test is less than 0.05 (a predetermined significance level), which again suggests that the null hypothesis can be rejected here. Overall, these results suggest that the IEL time series exhibit asymmetry.

Table 3.24: Data description of the daily IEL time series.

Statistics	No.Ob	Time span	Median	Min	Max	Mean	Stdev	Skewness *	Kurtosis*	Jarque – Bera test *
Iranian electricity load time series	1095	21/03/2007-20/03/2010	496.99	718.4	361.3	528.75	82.6	0.475 (0.99)	-0.90 (4.64e-10)	14.349 (0.00076)

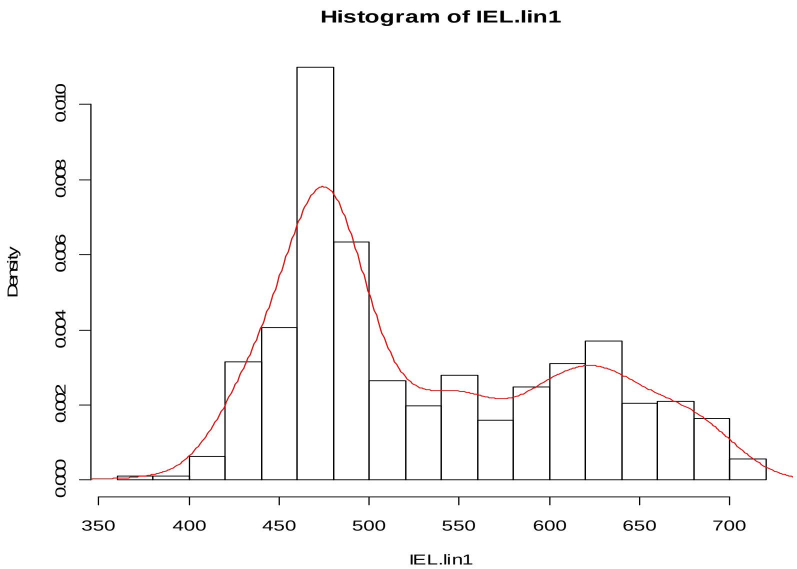


Figure 3.30: Histogram of the daily IEL time series (after detecting outliers).

Although the IEL time series does not clearly indicate seasonal behavior in Figure 3.31, a significant decrease in the variance of this time series after removing seasonal differences suggests that such behavior exists, according to Table 3.25. “nsdiffs” were applied as the seasonal unit root tests to determine the number of seasonal differences required for time series to be made stationary. In this function, the Canova-Hansen Test (1995) was employed, which resulted in its null hypothesis describing the deterministic seasonality of the time series (Hyndman and Razbash, 2014). In Table 3.26, the nsdiffs function demonstrates that it is accurate to evaluate the behavior of the IEL time series after taking the seasonal difference into account twice, increasing its stationary behavior. It might seem strange to do this twice, but Figure 3.29 also points to the annual cycling pattern of the IEL time series.

A periodogram of the IEL time series in Figure 3.32 is used to recognize the dominant cyclical behavior (periodic or frequency) of this time series (Penn State, 2014; Shumway and Stoffer, 2010). The dominant peak occurs close to 0.0027 in this diagram. The investigation of the periodogram value indicates that the peak occurs at nearly exactly this frequency. This corresponds to about 1/0.0027≈365 time periods, suggesting the annual cycling pattern of this time series; for more information, refer to PennState (2014) and Shumway and Stoffer (2010). By subtracting the seasonal difference from the yearly time series, the histogram diagrams exhibit a Gaussian-type distribution in Figure 3.33. Decreasing seasonality behavior is also observed in the IEL time series in Figure 3.34.

Table 3.25: Variance of the daily IEL time series after taking out seasonal differences.

Time series	Variance in IEL time series after detecting outliers	Varince in IEL time series after taking its seasonal difference	Variance in IEL time series after taking its first order difference
Iranian electricity load time series	6522.622	375.3487	452.885

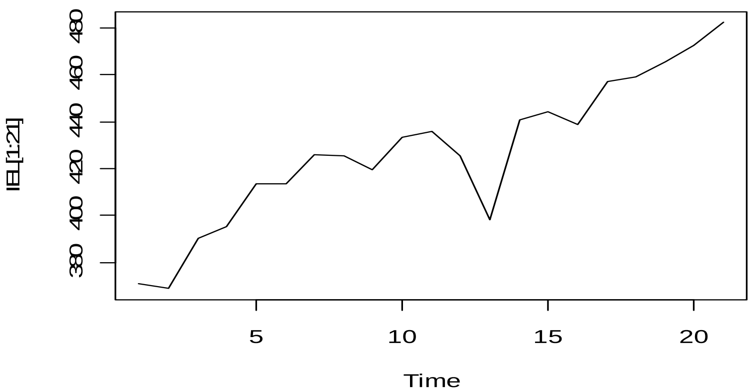


Figure 3.31: Seasonal behavior has shown in the IEL time series over 21 days.

Table 3.26: The results of “nsdiffs” in the daily IEL time series.

Nsdiffs function for Iranian electricity times series	**2**

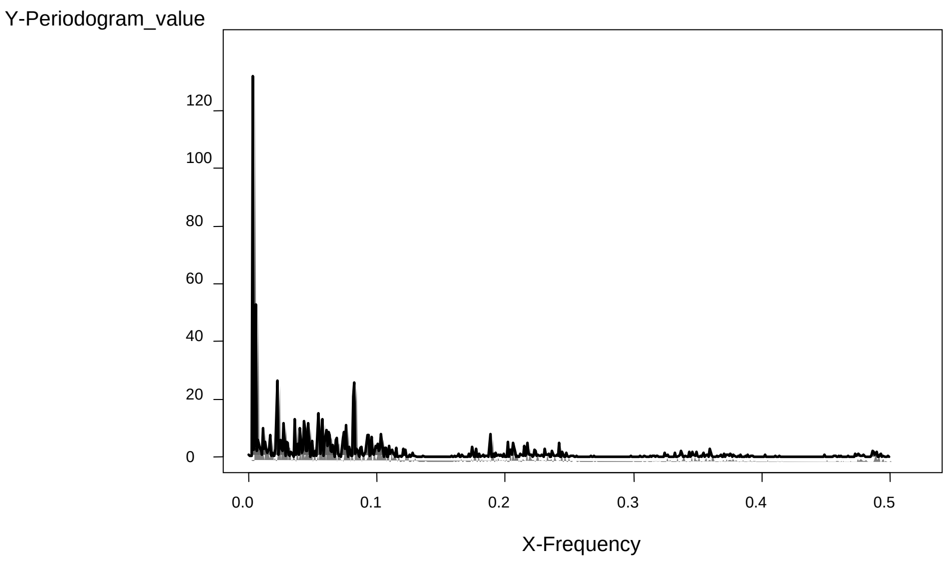


Figure 3.32: Periodogram of the daily IEL time series
(after taking out seasonal differences in order to demonstrate the yearly cycling patterns in this time series).

R-Code (19): Periodogram of the daily IEL time series.

Periodgram

```
par(mfrow=c(1,1))
ts.plot(diff(Iran_load,7))
FF = abs(fft(diff(Iran_load,7))/sqrt(1095))^2
Periodogram_value = ((3/1095)*FF[1:548])
Frequency= ((0:547)/1095)
plot(Frequency,Periodogram_value ,type="l")
```

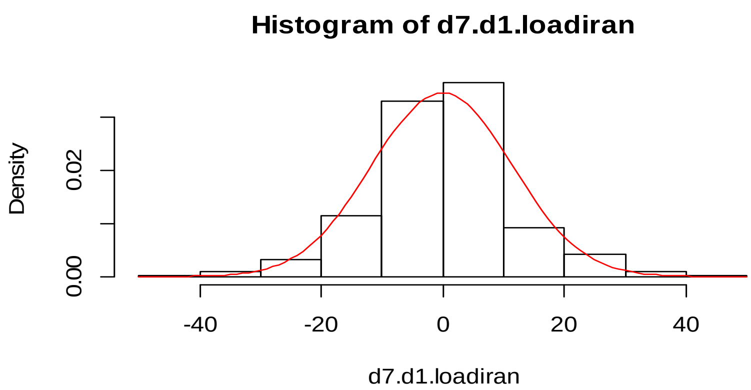


Figure 3.33: Histogram of the IEL
(after taking out seasonal difference and first order difference).

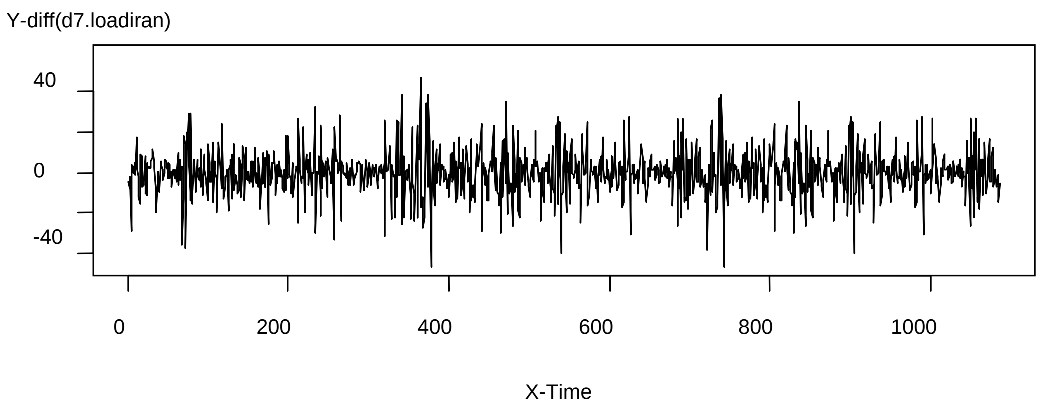


Figure 3.34: IEL time series behavior
(after taking out seasonal and initial non-seasonal differences).

The "Augmented Dickey Fuller" (ADF) Test was applied in order to examine whether the IEL time series was stationary after taking into account seasonal differences. Here, the null hypothesis determined the IEL series to be stationary rather than instable. The p-value derived from the ADF test is greater than 0.05 (the predetermined significance level), suggesting that the whole time series is stationary in Table 3.27. Therefore, the ADF test cannot be utilized, since the IEL demonstrates seasonality as well as cycling behavior over time; the IEL has the seasonality component shown in Table 3.25, as the variance of this time series significantly decreases after accounting for seasonal differences (Box et al., 1994; Cryer and Chan, 2008; Tsay, 2005).

Consequently, the Zivot and Andrews "Unit Root Test" was applied, in order to take into account any possible structural breaks. The null hypothesis is defined so that there is an existing unit root with a drift and/or break at an unknown point against the alternative hypothesis, which is a stationary trend with a break in an intercept or trend at an unknown point (Pfaff, 2008). For the IEL time series, the null hypothesis is rejected, because the test statistics value is less than the critical value at each significant confidence interval level (Pfaff, 2008); see Table 3.28. The conclusion is that a trend exists in this time series.

Table 3.27: Unit Root Test for the daily IEL (after taking out seasonal differences).

Test	for Iranian electricity load (IEL) time series after taking seasonal difference
ADF Test	Augmented Dickey-Fuller Test data: d7.loadiran Dickey-Fuller = -3.0642, Lag order = 50, p-value = 0.1278 alternative hypothesis: stationary

Table 3.28: Zivot and Andrews Unit Root Test results for the IEL time series.

Result of Unit root Test	Critical values at 99% confidence interval level	Critical values at 95% confidence interval level	Critical values at 90% confidence interval level
Test statistics value for Iranian electricity load time series (after taking seasonal difference)	Critical values		
-5.7438	-5.57	-5.08	-4.82

R-code (20): Zivot and Andrews test code and its results for daily IEL time series.

```
za.spain=ur.za(IEL.d7,model="both",lag=10)
summary(za.spain)

################################
# Zivot-Andrews Unit Root Test #
################################
Call:lm(formula = testmat)
Residuals:
    Min      1Q  Median      3Q     Max
-42.006  -5.113   0.258   5.430  49.880
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.713314   0.760369   0.938  0.34840
y.l1         0.870089   0.022618  38.469  < 2e-16 ***
trend       -0.002491   0.001781  -1.399  0.16222
y.dl1       -0.053263   0.034836  -1.529  0.12657
y.dl2       -0.043531   0.034623  -1.257  0.20893
y.dl3       -0.068598   0.034254  -2.003  0.04547 *
y.dl4        0.041667   0.029724   1.402  0.16127
y.dl5       -0.025763   0.029502  -0.873  0.38273
y.dl6       -0.005728   0.029164  -0.196  0.84432
y.dl7       -0.441177   0.028926 -15.252  < 2e-16 ***
y.dl8       -0.066135   0.031483  -2.101  0.03591 *
y.dl9       -0.034460   0.031146  -1.106  0.26881
y.dl10      -0.055597   0.030676  -1.812  0.07021 .
du           3.948237   1.328484   2.972  0.00303 **
dt          -0.011896   0.005508  -2.160  0.03100 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 9.833 on 1062 degrees of freedom
  (11 observations deleted due to missingness)
Multiple R-squared: 0.7412,     Adjusted R-squared: 0.7378
F-statistic: 217.3 on 14 and 1062 DF,  p-value: < 2.2e-16
Teststatistic: -5.7438
Critical values: 0.01= -5.57 0.05= -5.08 0.1= -4.82
Potential break point at position: 736
```

The autocorrelation function (ACF) and partial correlation function (PACF) are also employed to analyze this time series. Figure 3.35 shows the correlation between one variable at different times (Cryer and Chan, 2008; Tsay, 2005). ACFs and PACFs do not display any stationary behavior, even after taking out seasonal and first-order differences from the IEL time series; see Figure 3.35-C and D. Weak stationary behavior is found in each time series, which has led the researcher to utilize the ARIMA model in order to develop suitable models for IEL time series (Cryer and Chan, 2008; Tsay, 2005).

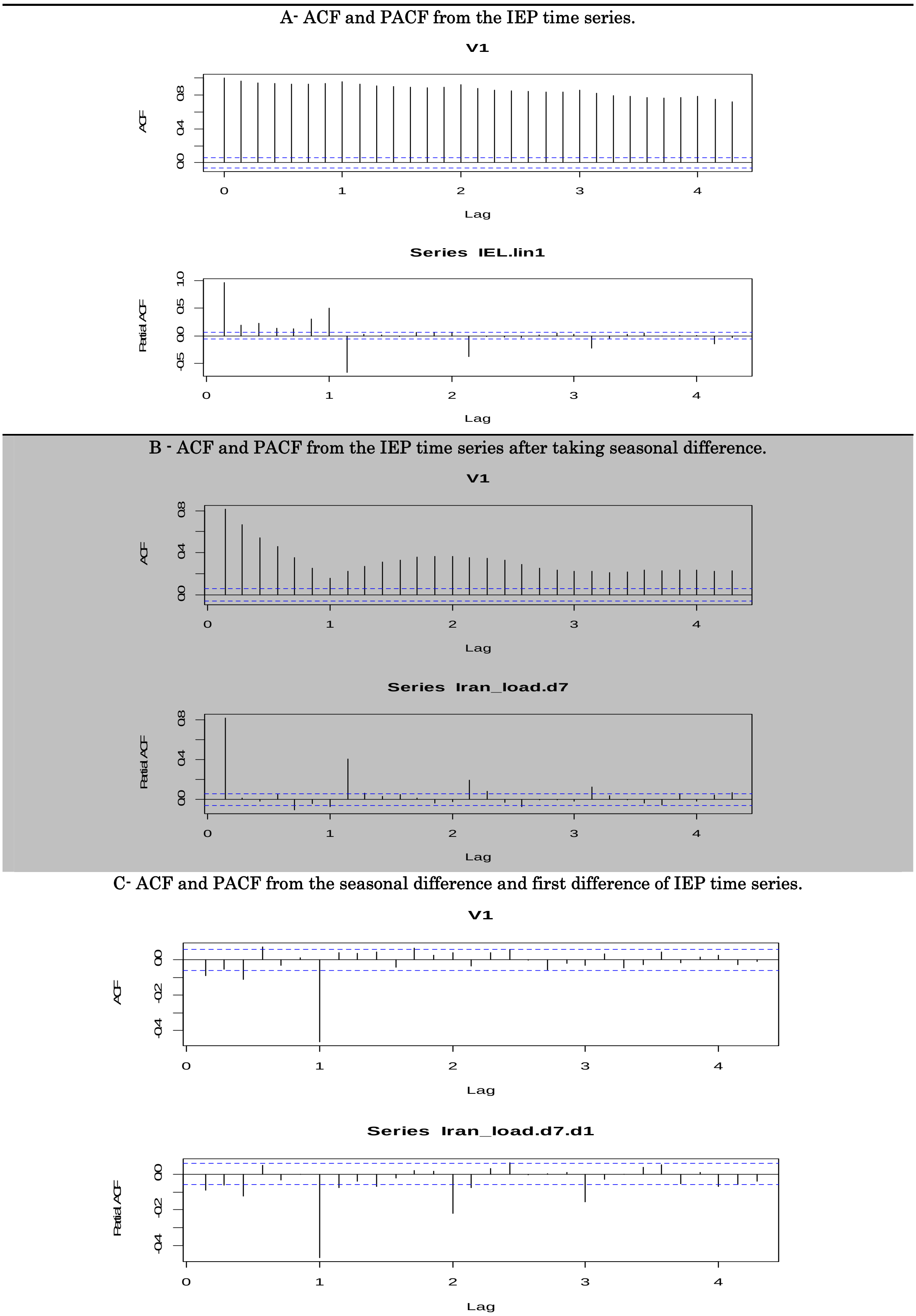


Figure 3.35: ACF and PACF from the daily IEL time series.

3.2.2 Time series modelling of Iranian electricity loads

3.2.2.A The ARIMA and SARIMA models

The data description defines the IEL time series as weakly stationary, even after subtracting its differences. Based on the time series analysis approach, the autoregressive integrated moving avaerage (ARIMA) model may be a suitable model for estimating this time series. Hence, the statistical equation of the model is presented in Table 3.29-A:

Table 3.29: The statistical equations of the ARIMA and SARIMA models for the IEL series.

Models	Iranian electricity load time series	MSE
A- ARIMA model	$(1\text{-}0.8430B_1 \text{-}0.0654B_2)(1\text{+}0.4564B_1)^7Yt = e_t$	97.84725
B- SARIMA model	$(1\text{+}0.90B_1 \text{+}0.0667B_{2\text{+}}0.1074B_3)(1\text{+}0.5076)^{52}Yt = e_t$	187.9855

Table 3.30: ARIMA and SARIMA models for the daily IEL time series.

Model for		"ARIMA Model and SARIMA models for Iranian electricity load time series"
Iranian electricity load time series.	A- ARIMA $(2,0,0)(1,1,0)_7$	Coefficients: ar1 ar2 sar1 0.8430 0.0654 -0.4564 s.e. 0.0305 0.0307 0.0278
		sigma^2 estimated is 98.48: log likelihood=-4042.1
	B- SARIMA (3,1,0,1,1,0,52) (Or ARIMA $(3,1,0)(1,1,0)_{52}$	Coefficients: ar1 ar2 ar3 sar1 -0.0900 -0.0667 -0.1074 -0.5076 s.e. 0.0312 0.0311 0. 0311 0.0270
		sigma^2 estimated is 197.6: log likelihood=-4212.03

One of the best ARIMA models in Table 3.30 is ARIMA $(2.0.0)(1,1,0)_7$, where the ϕ coefficients are associated with the autoregressive section (AR). Here, the coefficient related to ar1 and ar2 are significant because the p-values are greater than two in Table 3.30-A. The "Φ" Parameters are associated to B^s, which is in turn related to the seasonal AR section of the model, significant because the t-value is also greater than two. This in itself could be a good indication that the model is suitable, but the autocorrelation (ACF) and partial correlation function(PACF) of the squared residuals shows that there are several lags that they are above the confidence interval in Figure 3.36-A. The histogram and Q-Q plots in Figure 3.37-A demonstrate a large heavy tail. The results of the Ljung-Box Test also shows that after the second lags there is small dependency among of the residuals of the ARIMA model, as seen in Figure 3.38 (Cryer, 2008; Tsay, 2005; Dahyot, 2012).

The residuals analysis of these ARIMA estimate models indicates there is serials correlation among the residuals; see Figures 3.36-A and 3.39-A. This suggests the existence of volatility clustering in the residuals of this series (Tsay 2005; Hu 2011). These results prove that the ARIMA model is not suitable for clearly estimating the behavior of the IEL (Cryer, Jonathan D., Chan Kung-Sik, 2008; Tsay 2005; Box et al. 2013; S, Hu, 2011). The same analysis can be applied to the IEL time series.

Despite fitting a seasonal ARIMA model— the SARIMA model (p,d,q,P,D,Q,S) — to the time series, a similar result is obtained: i.e., volatility clustering in the residuals, as seen in Figures 3.37-B and 3.39-B. The SARIMA model has the same definition as the ARIMA model (see Eq. (3.12)), but the (yearly) cycling behavior is added to the model (Shumway and Stoffer, 2010), making the seasonal period equal to D (in the ARIMA model usually D is equal to one), see Eq.(3.3) and Eq.(3.12). Here, for the IEL time series the seasonal period is equal to 52 weeks per year (see Table 3.30-B). However, the ACF and PACF functions derived from the residual analysis of this model exhibit a serial correlation in the residuals; see Figure 3.36-B. Thus, due to conditional forecasting and temporal fluctuations in the data-variance, no (S)ARIMA model is capable of accurately modelling such a time series.

$$\phi(B)\Phi(B^S)(1-B^d)(1-B^D)Yt = \Theta(B^S)\theta(B)e_t \qquad \text{Eq.3.12}$$

In order to model these time series more accurately by investigating their residual patterns, the research turned to the ARMA-GARCH model (Cryer and Chan, 2008;Tsay, 2005; Wurtz et al., 2006).

A -Residuals analysis of the ARIMA estimated model for IEL time series.	**B** -Residuals analysis of the SARIMA model for IEL time series.

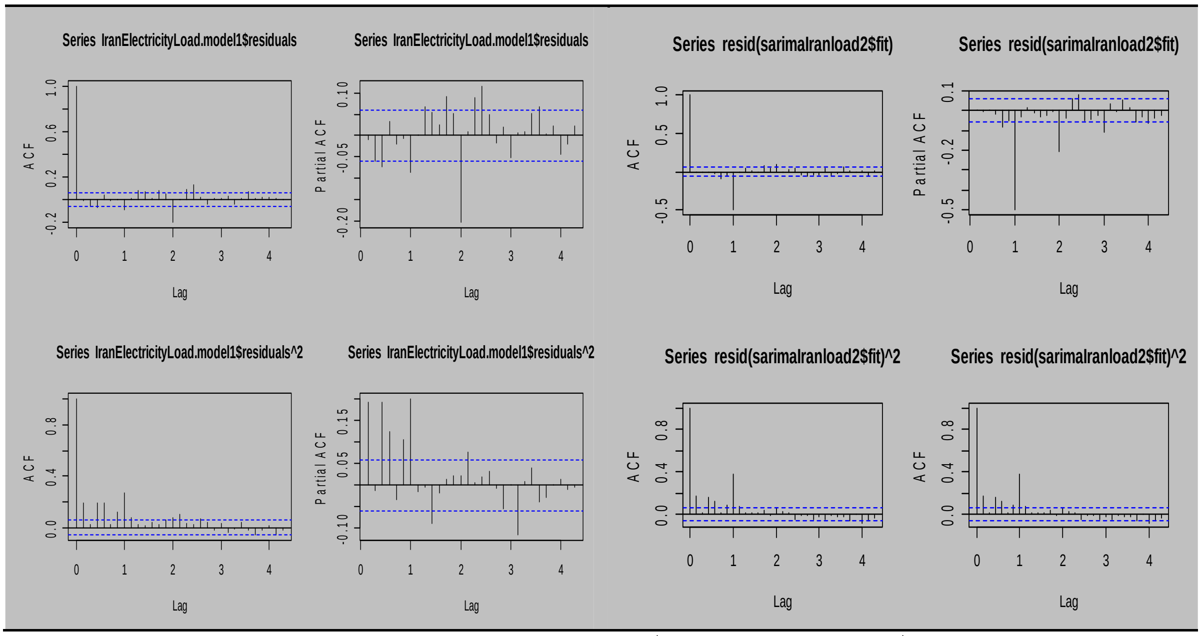


Figure 3.36: The ACF and PACF of the (regular and squared) residuals from the ARIMA and SARIMA models.

A-Q-Q plot and Histogram ARIMA model. B- Q-Q plot and Histogram SARIMA model.

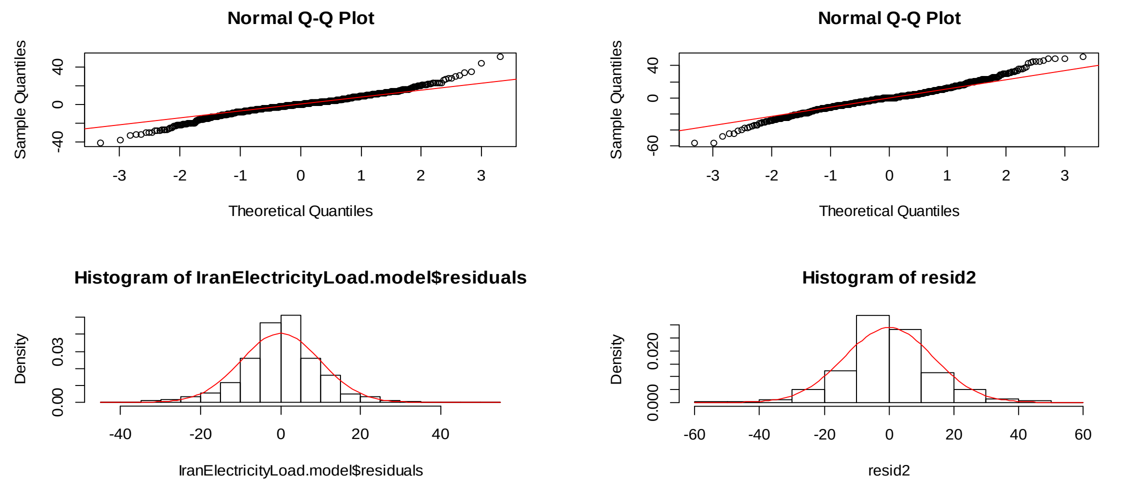


Figure 3.37: Q-Q plot and Histogram of the ARIMA and SARIMA models.

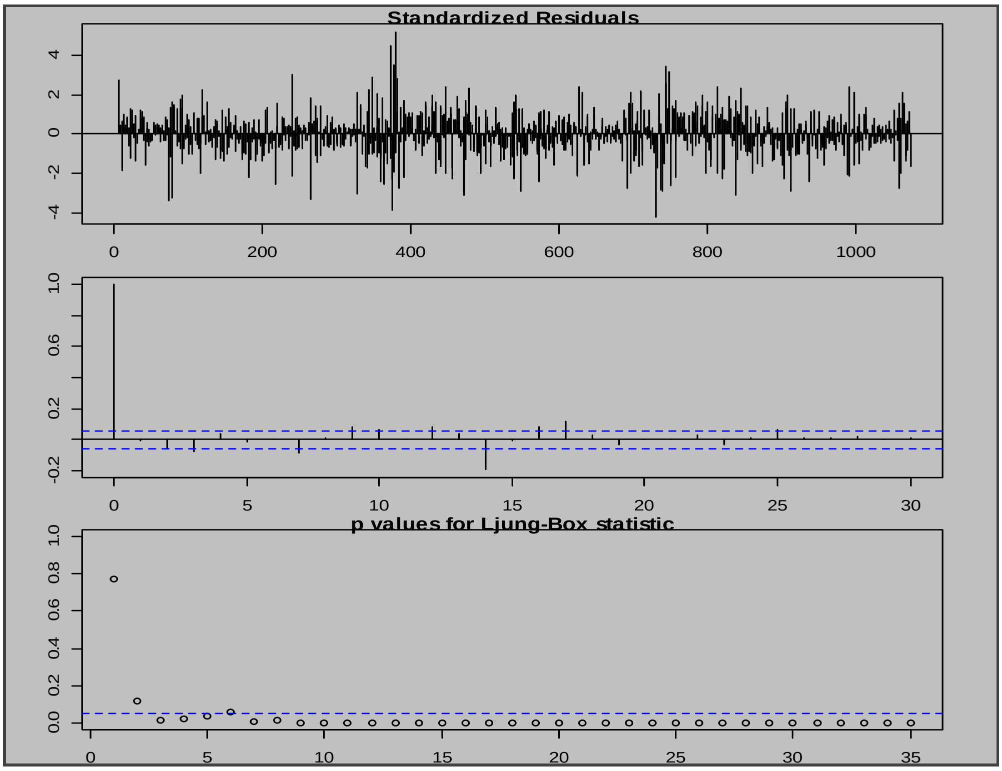


Figure 3.38: Ljung-Box Test of the ARIMA model related to the IEL time series.

R code (21): Diagnòstics Ljung-Box

```
win.graph()
par(mar=c(2,2,1,1))
tsdiag(IranElectricityLoad.model,gof.lag=50)
```

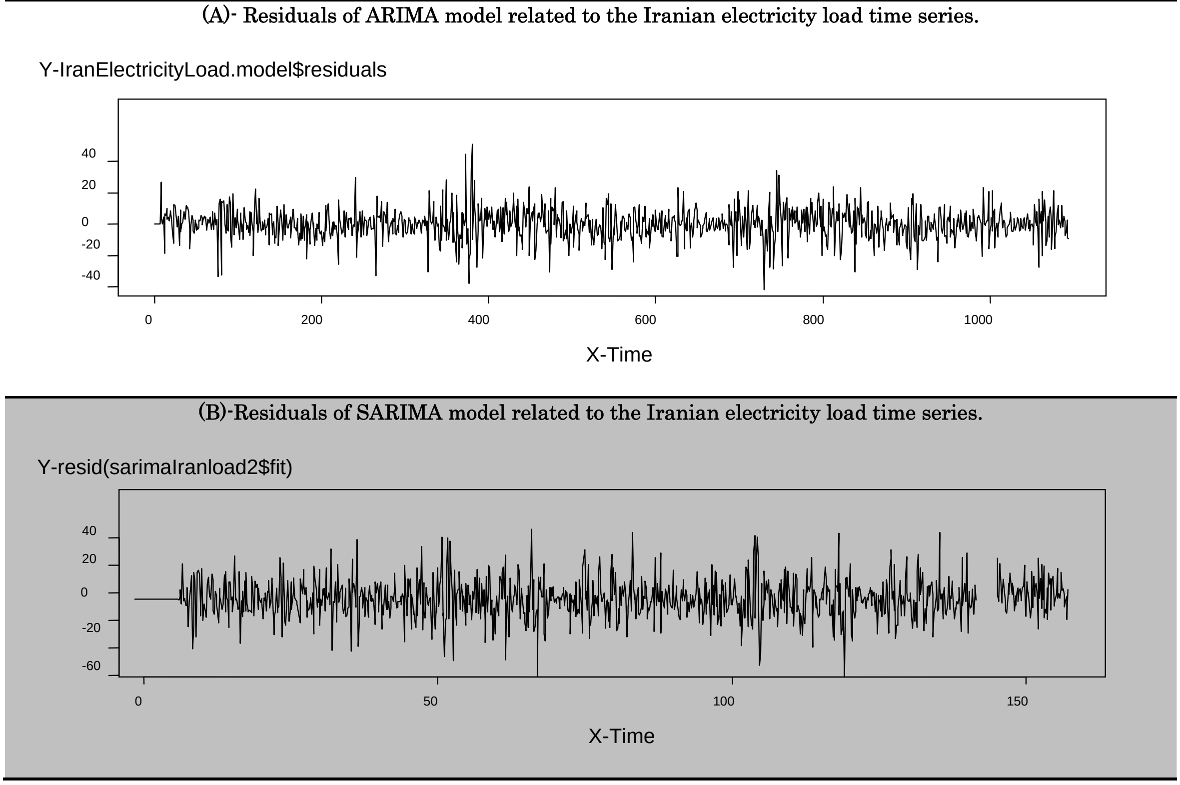


Figure 3.39: Behavior of residuals related to the ARIMA and SARIMA models in above.

3.2.2.B ARMA-GARCH model after taking out seasonal difference

The residual analysis of the estimated (S)ARIMA models for the IEL showed that these are not adequate models, proved by the serial correlations and a non-constant volatility condition existing in the data. In other words, there was a clear indication of the existence of volatility clustering in the residuals of the IEL series (Wurtz et al. 2006; Tsay, 2005; Cryer, 2008; Hu, 2011).

Therefore, again due to the existence of uncertainty (heteroscedasticity), temporal fluctuations and conditional predictions of the data-variance in the IEL time series, the ARIMA models are not well-suited to accurately analyzing the IEL time series (Cryer and Chan, 2008; Tsay, 2005; Wurtz et al., 2006). So, ARMA-GARCH models were applied in order to investigate and estimate these cluster patterns in the series, specifically the ARMA-GARCH, referred to as conditional heteroscedastic or non-constant variance models (Cryer and Chan, 2008; Wurtz et al., 2006; Tsay, 2005).

The ARMA-GARCH model is provided in Table 3.31. For increasing the accuracy of the estimations, the ARMA-GARCH model is calculated after taking out the seasonal differences from IEL time series. Table 3.32 demonstrates the results obtained from the Shapiro-Wilk Test, and the standardized residuals that they suggested, which state that the IEL time series do not follow a Gaussian distribution (Hu, 2011; Zhang, 2009). In particular, a poly-root function has been applied in order to find the zeroes of the polynomials in the AR part of the ARMA-GARCH model; see Table 3.33.

The results of these tests indicate that there are some kinds of polyroots in the model (Pfaff, 2008; Box, et al., 2008; Prasolov, 2009), because the roots of the AR polynomial in the model are equal one. According to the ACF and PACF plots shown in Figure 3.40-A, it seems that there is no volatility and serial correlation among the residuals. However, in the Q-Q plot and histogram shown in Figure 3.40-B, a large heavy tail can clearly be seen in the plots. This may suggest the existence of serial correlation (or volatility clustering) and there is no constant conditional variance. In other words, there is no any stationary condition (such as no constant mean variance) for the residuals distribution in this model.

Because of the yearly cycling behavior of IEL time series in Figure 3.32, in addition its seasonal behavior, it is necessary to take a differentiation of order one for this time series.

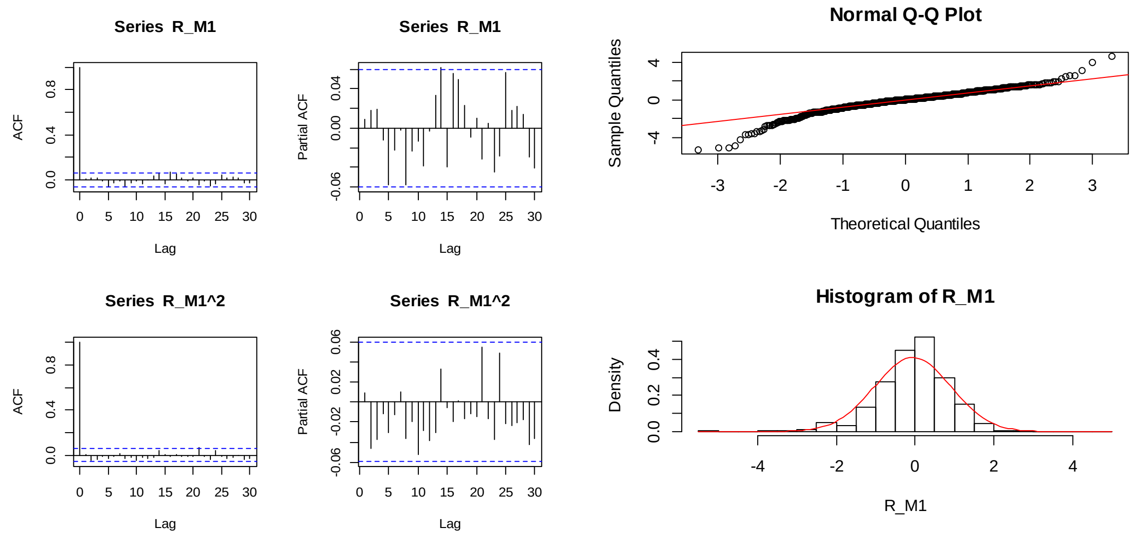
This is useful for increasing its non-stationary and conflicted behavior in the IEL time series in order to estimate another suitable ARMA-GARCH model (Shumway and Stoffer, 2010; Tsay, 2005; Cryer, et al., 2008), as shown in Table 3.34.

Table 3.31: Statistical equation of the ARMA-GARCH model for the IEL time series.

	ARMA-GARCH Model	MSE
For Iranian electricity load time series	$r_t - 0.9837\ r_{t-1} = a_t - 0.184086\ a_{t-1} - 0.13351\ a_{t-2} - 0.11042\ a_{t-3} - 0.6776\ a_{t-7} + 0.128\ a_{t-8} + 0.110\ a_{t-9} + 0.115\ a_{t-10}$ $a_t = \sigma_t \varepsilon_t$ $\sigma_t^2 = 5.4859 + 0.18871\ \varepsilon^2_{t-1} + 0.7889\ \sigma^2_{t-1}$	0.992377

A-ACF and PACF from the(regular and squared) residuals of the ARMA Garch model(related to IEL time series after taking sesonal difference).

B- The Q-Q plot and histogram of the ARMA-GARCH model of the IEL time series.



Note: **(A)**-The ACF and PACF of the (regular and squared) residuals of the ARMA Garch model. **(B)**-The Q-Q plot and histogram of the ARMA-GARCH model of the IEL time series.

Figure 3.40: **A**-Residuals analysis via ACF and PACF and **B**- histogram and Q-Q plot.

Table 3.32: The ARMA-GARCH model for the IEL time series
(after taking out seasonal differences).

```
R-code(21):
garchFit(formula = ~arma(1, 10) + garch(1, 1), data = d7.loadiran[1:1076],
    cond.dist = "std", trace = F)
```

```
GARCH Modelling
Error Analysis:
Coefficient(s):
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.034147    0.052805    0.647 0.517852
ar1     0.983736    0.006052  162.558  < 2e-16 ***
ma1    -0.184086    0.032767   -5.618 1.93e-08 ***
ma2    -0.133516    0.031413   -4.250 2.14e-05 ***
ma3    -0.110420    0.031916   -3.460 0.000541 ***
ma4     0.008096    0.020574    0.393 0.693957
ma5     0.005213    0.020644    0.253 0.800643
ma6    -0.018527    0.020715   -0.894 0.371102
ma7    -0.677633    0.023501  -28.835  < 2e-16 ***
ma8     0.128144    0.029534    4.339 1.43e-05 ***
ma9     0.110096    0.028716    3.834 0.000126 ***
ma10    0.115975    0.031169    3.721 0.000199 ***
omega   5.485920    2.676047    2.050 0.040364 *
alpha1  0.188714    0.049811    3.789 0.000152 ***
beta1   0.788955    0.056104   14.062  < 2e-16 ***
shape   3.825273    0.513093    7.455 8.97e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  914.0295  0
 Shapiro-Wilk Test  R    W      0.939874  0
 Ljung-Box Test     R    Q(10)  10.07657  0.4338011
 Ljung-Box Test     R    Q(15)  19.37088  0.1974167
 Ljung-Box Test     R    Q(20)  28.23109  0.1040408
 Ljung-Box Test     R^2  Q(10)  9.365199  0.4978307
 Ljung-Box Test     R^2  Q(15)  13.48472  0.5649122
 Ljung-Box Test     R^2  Q(20)  14.00673  0.8301546
 LM Arch Test       R    TR^2   12.15731  0.4331297
```

Table 3.33: Stationary univariate analysis of the ARMA-GARCH models.

R Code(22): Mod(polyroots(1,φ_i))	The poly roots of AR(p) polynomial in ARMA-GARCH Model
Iranian electricity load time series (after taking seasonal difference).	To estimate the root of AR(1) polynomial -Process with φ_1= ,-0.983: 1.016437

3.2.2.C ARMA-GARCH model (seasonal and first-order differences)

Here, the ACF and PACF plots shown in Figure 3.41-B display no volatility or serial correlation among the residuals, so this modeling approach is valid; see Table 3.35 (Cryer and Chan, 2008; Tsay, 2005). The Q-Q plot and histogram of the residuals analysis of this model show that there is a very low heavy tail in Figure 3.41-A. According to Table 3.34, the results of Shapiro-Wilk indicate standardized residuals, a suggestion that in this model the time series also does not follow a Gaussian distribution (Hu, 2011; Zhang, 2009). Furthermore, the poly root function was applied in order to find the zeroes of polynomials in the AR part of this developed ARMA-GARCH model; see Table 3.36. The results of this test indicate that there are no roots of any kind in this model (Pfaff, 2008; Box, et al., 2008; Prasolov , 2009), which also verifies the validity of the developed model.

Table 3.34: ARMA-GARCH model for the IEL time series (after taking out seasonal and first-order differences).

```
R-code(23):
M2_GARCH_R=garchFit(~arma(2,8)+garch(1,1),data=d7d1.loadiran[1:1073],trace=F,cond.dist="std")
; summary(M2_GARCH_R)
```

```
GARCH Modelling
Error Analysis:
Coefficient(s):
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.014344    0.019000    0.755 0.450271
ar1     0.683035    0.058359   11.704  < 2e-16 ***
ar2    -0.022227    0.045521   -0.488 0.625347
ma1    -0.877191    0.049769  -17.625  < 2e-16 ***
ma2     0.029293    0.035531    0.824 0.409700
ma3     0.007504    0.026401    0.284 0.776235
ma4     0.018222    0.026085    0.699 0.484833
ma5    -0.005885    0.025185   -0.234 0.815250
ma6    -0.020071    0.027125   -0.740 0.459315
ma7    -0.661868    0.027913  -23.712  < 2e-16 ***
ma8     0.594256    0.033698   17.635  < 2e-16 ***
omega   6.603425    3.499353    1.887 0.059155 .
alpha1  0.193589    0.053173    3.641 0.000272 ***
beta1   0.768786    0.069551   11.053  < 2e-16 ***
shape   3.977012    0.539049    7.378 1.61e-13 ***
---Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  808.3885  0
 Shapiro-Wilk Test  R    W      0.9428116 0
 Ljung-Box Test     R    Q(10)  5.315339  0.8691425
 Ljung-Box Test     R    Q(15)  14.49732  0.4881937
 Ljung-Box Test     R    Q(20)  21.61643  0.3616816
 Ljung-Box Test     R^2  Q(10)  11.01255  0.3565411
 Ljung-Box Test     R^2  Q(15)  15.49436  0.416428
 Ljung-Box Test     R^2  Q(20)  16.21135  0.7034287
 LM Arch Test       R    TR^2   13.37503  0.3423811
```

Table 3.35: The statistical equation of ARMA-GARCH model (after taking out seasonal and first-order differences of IEL time series).

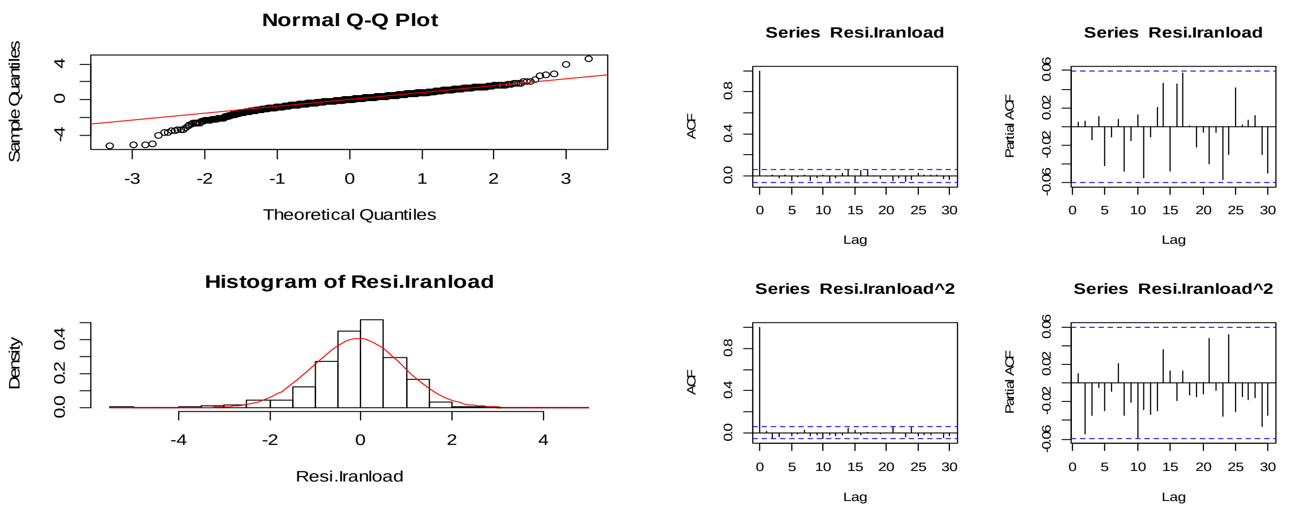
Model for	ARMA-GARCH model	MSE
Iranian electricity load After twice time its taking (non) seasonal difference time series.	$r_t - 0.68302\, r_{t-1} + 0.022227\, r_{t-2} = a_t - 0.877191\, a_{t-1} - 0.661868\, a_{t-7} - 0.5942\, a_{t-8}$ $a_t = \sigma_t \varepsilon_t$ $\sigma^2 = 6.6034 + 0.765 + 0.1935\, \varepsilon^2 + 0.768\, \sigma^2{}_{t-1}$	0.9580401

Table 3.36: Stationary univariate analysis of the ARMA-GARCH models.

R Code(24): mod(polyroots(1,φ_i))	The poly roots of AR(p) polynomial in ARMA-GARCH Model
Iranian electricity load time series	To estimate the root of AR(1) polynomial -Process with φ_1= 0.69: 1.449275

A- The Q-Q plot and histogram of the ARMA-GARCH model of the IEL time series.

B- ACF and PACF from the(squared) residuals of the ARMA Garch model(after taking sesonal and first order difference).



Note: (A)- The Q-Q plot and histogram of the ARMA-GARCH model residuals. (B)- The ACF and PACF from the (regular and squared) residuals of the ARMA-GARCH model.

Figure 3.41: Residuals analysis via ACF and PACF, histogram and Q-Q plot.

3.2.3 Results

3.2.3.A Comparison of the Iranian electricity load estimated models

Table 3.37 provides a comparison of all the models related to the IEL time series. Here, the ARMA-GARCH model (after taking out the seasonal and first-order differences from the time series) was determined to be one of the most suitable models. It is able to represent an adequate estimation of the behavior patterns of load in Iran. In this table, no significant difference can be observed among the mean square error of two ARMA-GARCH models.

The existence of unit roots in our first estimated ARMA-GARCH model is the only difference between them. Other models, such as the classic ARIMA model and the SARIMA model, did not perform a suitable prediction, mainly due to the volatility of the residuals.

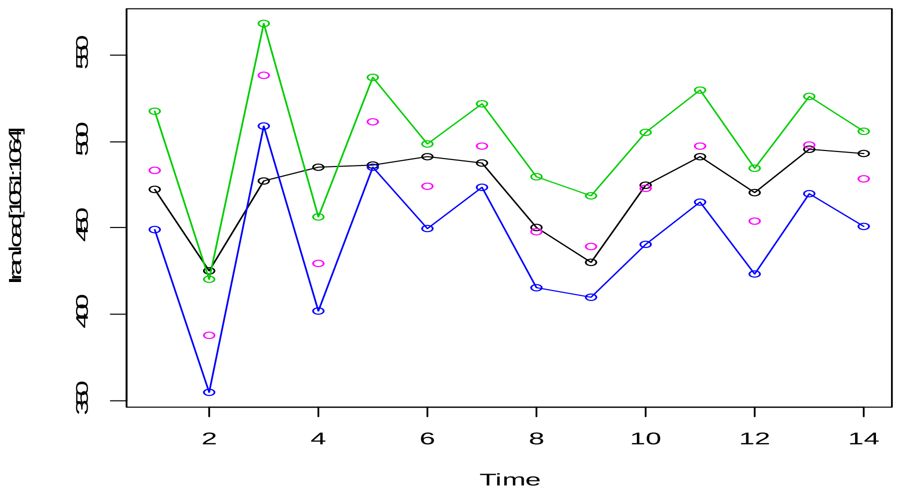
Table 3.37: Comparison of estimated models for the IEL time series.

Models	Model validation	Residuals validation	Time series in model	MSE
ARIMA model	Valid	volatility	Iranian electricity load time series	96.78328
SARIMA model	Valid	volatility	Iranian electricity load time series	187.9855
ARMA-GARCH model	Valid	polyroots	Iranian electricity load time series (after taking seasonal difference)	0.946364
ARMA-GARCH model	Valid	No volality No polyroots	Iranian electricity load time series (after taking seasonal difference and its first order difference)	0.9580401

3.2.3.B Prediction in sample of the IEL time series

This part of the thesis evaluated the daily forecasting for the IEL over 14 days. An in-sample prediction was made using the ARMA-GARCH model after taking out seasonal and first-order differences from the IEL time series; see Figure 3.42 and Table 3.35. Daily predictions were within the 95% confidence interval 95%. This prediction in sample was performed from the 1051st to the 1064th day. The sample forecasting has had very similar behavior using real data.

Therefore, it can be confirmed that this model is the most suitable model for making a proper estimation of the behavior of the load in Iran. Similar to the Iranian electricity price (IEP), an out-of-sample forecasting for Iranian electricity loads (IEL) will be provided in Chapter 4. This forecasting is evaluated through a simulation for the ARMA-GARCH model (for more detailed information, see Chapter 4).



Note: Red points in the figure indicate forecasting. Black points and lines indicate the real price. Green and blue points and lines indicate confidence intervals.

Figure 3.42: IEL forecasting in sample over 14 days (1051st to 1064th) using the ARMA-GARCH model.

3.3 Time series analysis of Spanish electricity prices

This section is divided in three parts: the first, related to a data description of the Spanish electricity price (SEP) time series. The second part represents the modelling of the SEP time series analysis. The final section compares the models and makes a prediction in sample.

3.3.1 Data description of Spanish electricity prices

As explained in Chapter 2, after the Spanish electricity market (MIBEL) was established in 2007, some rules were enacted for the day-ahead, intraday and renewable electricity markets (Ciarreta et al., 2014; Muñoz et al., 2013; Corchero, 2010; Weron, 2007). This was useful in improving earlier mechanisms of the Spanish electricity market and has converted it into a more competitive market. As previously mentioned, Spain's electricity market has been deregulated since 2007. Generally-speaking, the new Spanish market initiates general operations, and then all the generators, distributors, commercialization companies and end consumers carry out negotiations in the spot electricity market (see Muñoz, Corchero and Heredia, 2013; Corchero, 2010; Gonzalez and Basagoiti, 1999; Muñoz and Dickey, 2009).

In contrast to the Iranian electricity market, the operators in the Spanish electricity market consider "bids for accepting generator companies in the spot markets", and they can examine whether these agents can pass some conditions in the Day-Ahead market" (Muñoz et al., 2013; Corchero, 2010). The Spanish electricity market is a bilateral market (Gonzalez and Basagoiti, 1999; Corchero, 2010; Weron, 2007), where prices are determined by the spot price; namely, the aggregated demand at a certain hour and where the price elasticity of demand is not zero, as explained by Weron (2007) and Muñoz et al. (2013). In this market, companies have the ability to present their price to the market, clearly indicating it as a benchmark (Muñoz et al., 2013; Corchero, 2010; Ofgem, 2013; Weron, 2007).

Price is one of the main components of the electricity market (Weron, 2007). Furthermore, the current volatility of the financial markets make price behavior patterns very difficult to predict, especially in the case of electricity (Muñoz and Dickey, 2009), which cannot be stored. Therefore, the research in this thesis also presents a descriptive analysis of the Spanish electricity spot price time series, which is similar to the IEP time series. It covers three years of the SEP time series in Figure 3.43. The period of the daily data starts on July 1, 2007 and ends on September 30, 2010.

The data is represented by the "Spanish market operator" (2010). The price has been reported daily in order to investigate its behavior according to a suitable model during this study. Consequently, the valid prices exhibit an indication of the total behavior during a 24-hour period. There is a total of 1188 SEP samplings. The "R" programming software was used as a statistical analysis tool (R Development Core Team, 2011a).

Overall, the SEP plot shows daily upward drifts. This systematic pattern occurs for approximately the first 600 observations in the time series, and then the SEP exhibits a downward tendency in the observations. Again, this behavior pattern occurs in the last part of the time series; see Figure 3.43.

On the other hand, although this time series has high spikes and jumps in some area, there is just one span that has noticeably decreasing jumps. These occur at around two months, starting in the middle of February and continuing until the middle of March 2010. According to Figure 3.44, the high volatility observed in the price could be due to the increased electricity generation by wind power (Ketterer, 2014).

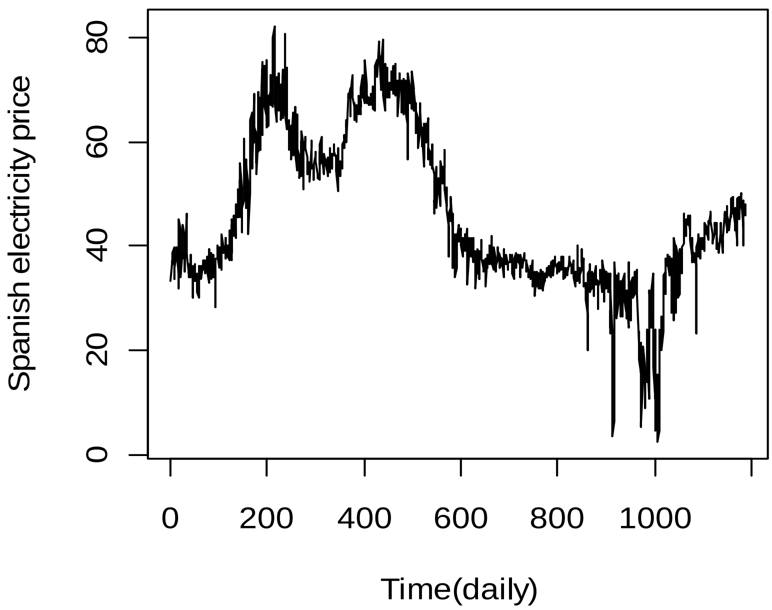
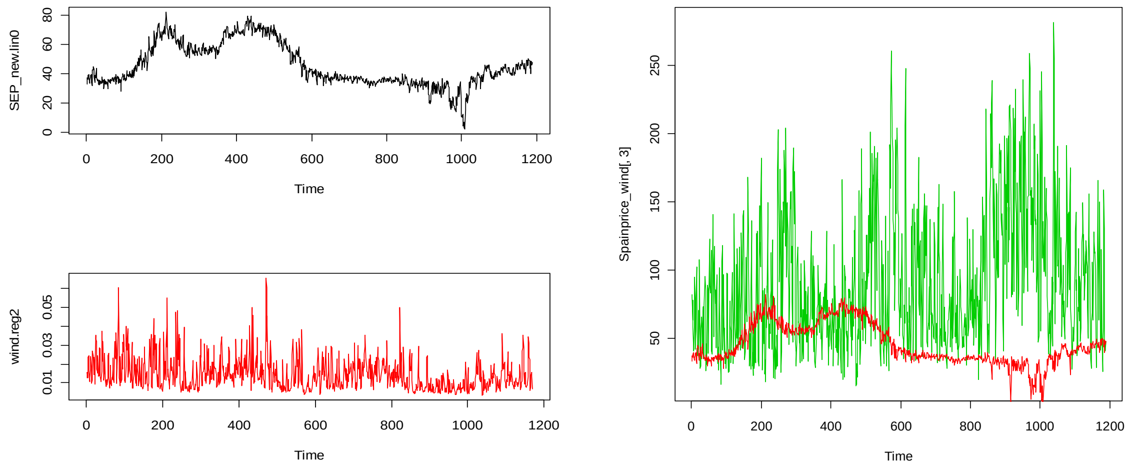


Figure 3.43: Daily Spanish electricity prices (SEP) (2007-2010).

The oscillations appear close to the upward trend and may be a sign of seasonal behavior in the SEP, as shown in Figure 3.44. The tendency of this observation variance reverts to a mean level. However, in order to obtain a suitable estimate from the data, the logarithm as a transformation function is not calculated out here in the SEP time series.



Note: **(A)**- daily SEP after detecting outliers (black line) and daily Spanish wind power generation (red line), scale: Inverse of wind divided by 1000. **(B)**- Comparison between SEP time series (green line) and Spanish wind power generation (red line). Time is shown by the order of observation in each daily series.

Figure 3.44: Daily SEP price and daily Spanish wind power generation.

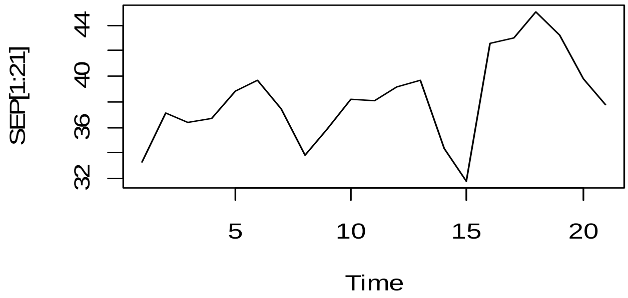


Figure 3.45: 21 days in the SEP time series.

According to Table 3.38, it can be proven that the Spanish electricity market does not have any Gaussian distribution, even after being linearized; see Figure 3.46-A, where the mean and the median of the data do not have the same value. However, the p-value of the skewness test is greater than 0.05, it means that it is equal to zero and matching with the skewness of the Gaussian distribution. On the other hand, the p-value in the Kurtosis test is less than 0.05. In addition, the Jarque-Bera Test on the SEP time series demonstrates that no normal distribution exists (Bai and Ng, 2005). The null hypothesis of the Jarque-Bera Test is thus rejected, because the test statistics value (p-value) is less than the critical value (0.05) at the 95% significant confidence interval level. This means that the skewness is not equal to zero, and/or the kurtosis is not equal to three. The histogram of the data in Figure 3.46-B also demonstrates that there is no single (normal) identification distribution.

Table 3.38: Summary description of the daily SEP time series.

Statistics	No.obs	Time Span	Median	Min	Max	Mean	Stdev	Skewsnes	Kurtosis	Jarque-bera Test
Spanish electricity price	1182	1/7/2007-30/9/2010	40.329	2.46	82.13	45.68	14.91	0.3094 (0.9999)	-0.4905 (0.00027)	30.7102 (2.145e-07)

The autocorrelation function (ACF) and partial correlation function (PACF) of the SEP time series in Figure 3.47-A show a slow positive decline over time. In other words, they indicate the correlation between one variable at different times (Cryer and Chan, 2008; Tsay, 2005). Here there is not even a weak stationary series, because all of the lags take place out of the 95% confidence interval level. This means that the ACFs and PACFs do not display any stationary behavior, even after taking out the first-order difference in SEP time series. Consequently, there is a weak stationary behavior in the time series, as seen in Figure 3.47-B.

It would also seem there is a seasonal cycling pattern in the observations; see Figure 3.47-B. This has led the researcher to calculate the seasonal differences of the time series prior to estimating the model for the SEP time series. That is, the SEP demonstrates seasonality as well as cycling behavior over time, as shown in Figure 3.45. It has a seasonality component, according to Table 3.39, as the variance of this time series decreases significantly after taking out seasonal differences (see Box, Jenkins and Reinsel (1994); Cryer and Chan (2008); Tsay (2005)). By subtracting the seasonal differences from the SEP time series, the histogram almost exhibit a Gaussian-type distribution, shown in Figure 3.48-A.

A-SEP time series after detecting its outliers (linearized). **B- Histogram of daily SEP after detecting outliers.**

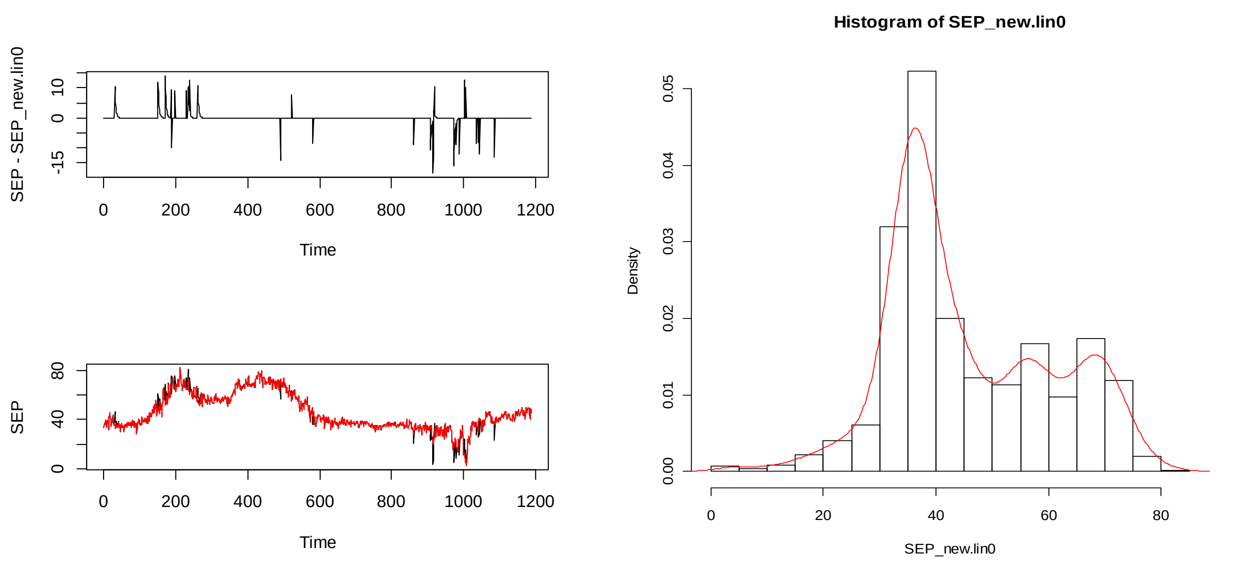
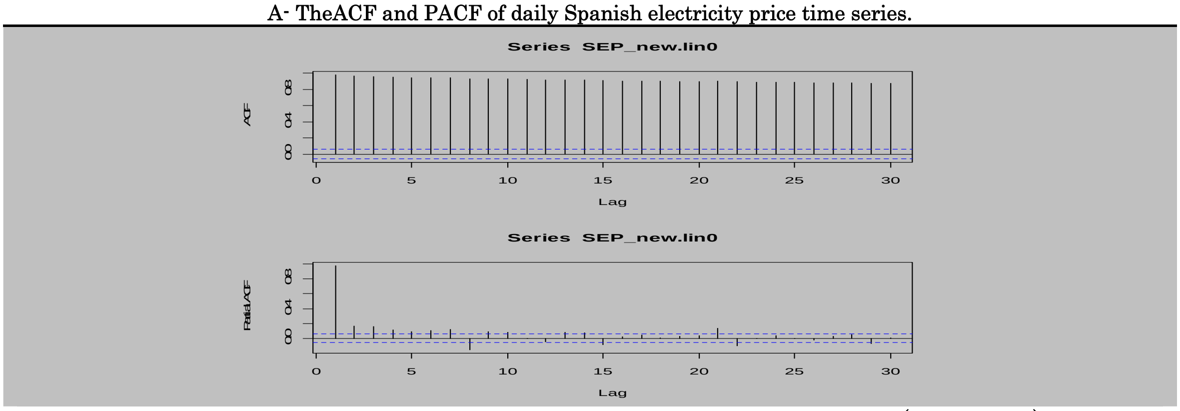


Figure 3.46: Detecting the outliers and histogram;
(A) Detecting the outliers of the SEP time series. (B) The histogram of the daily electricity price (2007-2010).

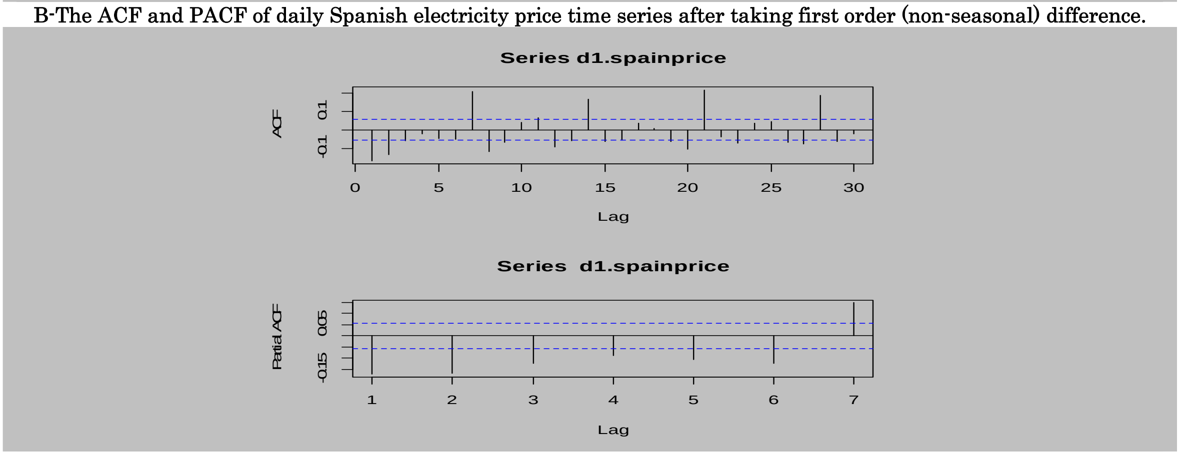
Table 3.39: Variance in the Spanish electricity price
(and its time series after taking out seasonal and non-seasonal (first-order) differences).

Variance in the Spanish electricity price time series.	212.1891
Variance in Spanish electricity price after seasonal difference.	23.58522
Variance in the Spanish electricity price after taking seasonal difference and taking the first order non seasonal difference.	13.71182

A- TheACF and PACF of daily Spanish electricity price time series.



B-The ACF and PACF of daily Spanish electricity price time series after taking first order (non-seasonal) difference.



C- TheACF and PACF of daily Spanish electricity price time series after taking seasonal difference.

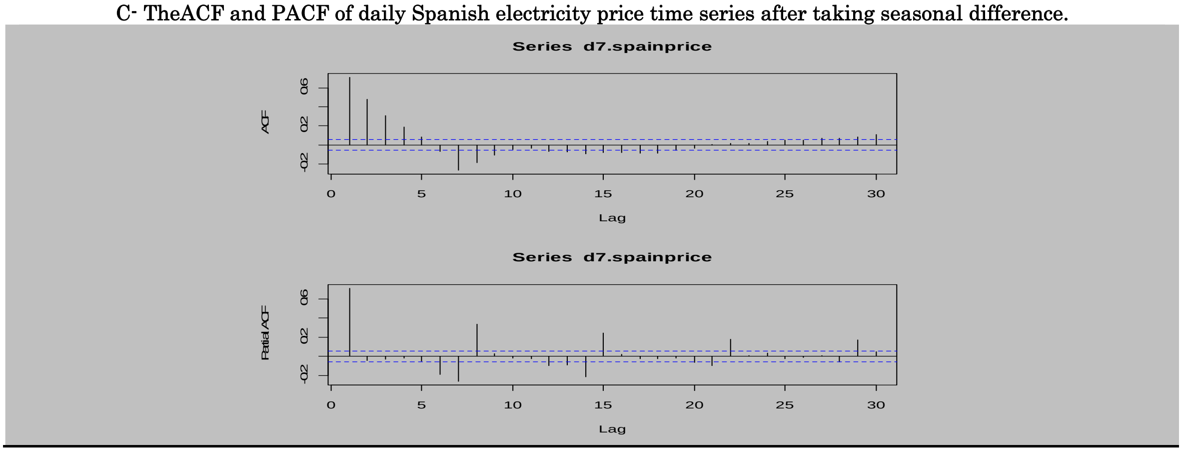


Figure 3.47: The ACF and PACF of the daily SEP time series.

A- The histogram of daily Spanish electricity price time series.	B-The Spanish electricity load time series after taking seasonal difference.

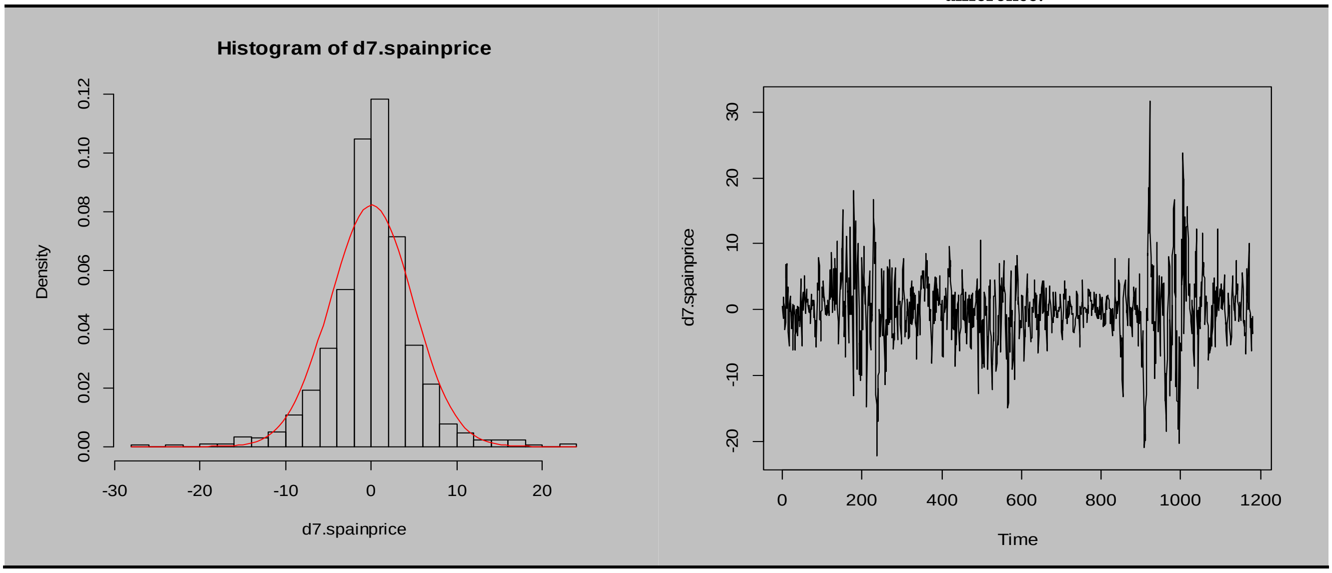


Figure 3.48: Histogram and SEP after seasonal difference; (A)- Histogram of the daily SEP time series. (B)- SEP time series after taking out seasonal differences.

Here, the "Augmented Dickey Fuller" (ADF) test was applied in order to examine whether or not the SEP time series is stationary (Narzo et al., 2008; Tsay, 2005), even after taking out seasonal differences, as shown in Table 3.40. In this case—a similar approach to that used for the IEP and IEL time series—the null hypothesis is that the time series is stationary, against the alternative that it is not. The p-value derived from the ADF test is less than 0.05, a predetermined significance level suggesting that the whole time series is stationary.

In contrast with this result, the Zivot and Andrews Unit Root Test was used in order to take into account any possible structural breaks in the SEP time series (Tsay 2005; Pfaff 2008). Here, the null hypothesis is rejected because the test statistics value is less than the critical values at each significance confidence interval level, as demonstrated in Table 3.41. Overall, it can be derived from these results that beyond the seasonal cycling pattern in the SEP, there is a similar trend in the time series. These properties can provide rather odd results in the time series analysis approach, because trend and seasonal cycling behavior exist in the time series at the same time.

Table 3.40: Augmented Dickey-Fuller test from the daily SEP time series.

Test	For Spanish electricity price time series.
ADF test	R-code(25): adf.test(d7.spainprice) Augmented Dickey-Fuller Test data: d7.spainprice Dickey-Fuller = -9.4484, Lag order = 10, p-value = 0.01 alternative hypothesis: stationary

Table 3.41: Zivot and Andrews Unit Root test, after seasonal differences.

Result of Unit root test	Critical values at 99% confidence interval level	Critical values at 95% confidence interval level	Critical values at 90% confidence interval level
Test statistics value for Spanish electricity price time series After taking its seasonal difference		Critical values	
-10.3691	-5.57	-5.08	-4.82

R-code (26): Zivot and Andrews Unit Root Test R-code and results in the SEP time series.

```
 za.spain=ur.za(d7.SEP,model="both",lag=10)
summary(za.spain)
################################
# Zivot-Andrews Unit Root Test #
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.2866401  0.2339827   1.225 0.220807
y.l1         0.6298135  0.0376668  16.721  < 2e-16 ***
trend       -0.0007533  0.0004051  -1.859 0.063223 .
y.dl3        0.0946589  0.0377135   2.510 0.012211 *
y.dl4        0.1153892  0.0331442   3.481 0.000517 ***
y.dl5        0.1387186  0.0328739   4.220 2.64e-05 ***
y.dl6        0.1676974  0.0324881   5.162 2.88e-07 ***
y.dl7       -0.2648623  0.0320448  -8.265 3.79e-16 ***
du           2.2812568  0.6053768   3.768 0.000173 ***
dt          -0.0127821  0.0052228  -2.447 0.014538 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Multiple R-squared: 0.5466,     Adjusted R-squared: 0.5411
F-statistic: 99.47 on 14 and 1155 DF,  p-value: < 2.2e-16
Teststatistic: -9.8279
Critical values: 0.01= -5.57 0.05= -5.08 0.1= -4.82
Potential break point at position: 1001
```

This unusual behavior also is shown in Figure 3.47-C, even after taking out seasonal and first-order differences in order to decrease the non-stationary behavior in the SEP time series. There are significant peaks at lag 7, 14, 21, etc., which means that one lag stands outside the confidence interval levels after every 6 lags, even after taking out seasonal difference from the SEP time series. These results suggest the existence of weekly seasonal unit roots in our time series.

Because of the variety of results attained using the time series analysis approach to the SEP time series, the Hegy Test was employed—first applied by Hylleberg in 1990. This seasonal unit root testing procedure is based on the expansion of the characteristic polynomial of its roots (Serrano, 2001). Under the null hypothesis of the Hegy Test, there are single unit roots, or there is zero frequency, against the frequency complex of seasonal unit roots, or the frequency is not zero (Serrano, 2001; Lopez-De Lacalle, 2013). Under the null hypothesis, the Hegy Test assumes that the relevant variable is seasonally integrated. Thus, the daily frequency is considered to have a weekly seasonal component in the observations.

Therefore, the test procedure assumes that the series can be determined via the DGP, given by $(1\text{-}B^7)\ y_t=\varepsilon_t \sim iid(0,\sigma_t^2);t=1,..,T$.

The character polynomials of this process can then be factorized as (1-B)S(B), where $S(B)=(1+B+...+B^6)$ is the seasonal moving average filter. Under the null hypothesis, it is assumed that the variable has a single unit root at the zero frequency and three pairs of complex roots at the seasonal frequencies of $k\ \omega;k=1,2,3;\omega=2\pi/7$. Notice that k represents the number of cycles per week of each frequency. Therefore, the seasonal unit roots testing procedure is based on the expansion of the characteristic polynomial of its roots, determining the following auxiliary regression, Eq.(3.13) (Rubia, 2001):

for $\varepsilon t \sim iid(0,\sigma_t^2)$

$$\Delta_7 Y_7 = \alpha + \beta t + \sum_{j=2}^{7} a_j D_{jt} + \sum_{j=2}^{7} \gamma_j D_{jt} t + \sum_{j=1}^{p} \pi_j z_{jt-1} + \sum_{r=1}^{7} \varphi_r \Delta_7 y_{t-r} + \varepsilon_t$$

Eq. 3.13

Where D_{jt} is a zero/one dummy corresponding to j-th day of the week and each of the regressors Z_{jt} are defined in the seasonal frequencies $\{k\omega;\ k=1,2,3;\omega=2\pi/7\}$ as follows:

$$Z_{1t} = \textstyle\sum_{j=1}^{7} \cos(0j) B^{j-1} y_t = S(B) y_t\,;$$

$$z_{2k,t} = \sum_{j=1}^{7} \cos(kj\omega)\, B^{j-1} y_t\ ;$$

$$z_{2k+1,t} = \sum_{j=1}^{7} \sin(kj\omega)\, B^{j-1} y_t\ ;$$

Eq. 3.14

The auxiliary regression in Eq. (3.13) reflects the most general specifications under the alternative stationary hypothesis. This specification includes a drift, a linear time trend, deterministic seasonal variables and seasonal drifts. The alternative specification of the test could include different combinations of these deterministic terms, either all, some or none of them (Rubia 2001; Serrano 2001).

Here, for Spanish electricity time series, the Hegy Test proves that some seasonal unit roots exist in the time series, as the p-value is less than 0.05 in Table 3.42. As result, the seasonal order difference must be taken out from the time series. This is because it decreases the daily frequency with a weekly seasonal component in the SEP time series, which thus points to some suitable steps in estimating the adequate SEP model.

Table 3.42: HEGY test – weekly seasonal unit root test for the SEP time series.

HEGY test results	Null hypothesis : Daily Spanish electricity price time series after first seasonality difference has single unitroots against weekly seasonality unit roots
Test statistic value (The level of the confidence intervals is 95%).	8.28e-08 ***

3.3.2 Time series modelling of Spanish electricity prices

3.3.2.A ARIMA model

Overall, these results suggest that there is no stationary behavior in the SEP time series. This means the ARIMA model may be introduced as an adequate model to represent a suitable estimation of the SEP time series behavior (Tsay, 2005). Here, the ARIMA model of the daily SEP is estimated in Table 3.43:

Table 3.43: Estimated model for the daily SEP time series.

The ARIMA Model for Spanish electricity price time series		
R-Code (26): `sp_p.mod1=arima(SEP_new.lin0[1:1169],order=c(8,0,0),fixed=c(NA,0,0,0,NA,0,NA,NA,NA,NA),seasonal=list(order=c(1,1,0),period=7),xreg=wind.reg2 )`		
Spanish electricity pricetime series	ARIMA (NA,0,0,0,NA,0,NA,NA,NA,NA)$(1,1,0)_7$	Coefficients: ar1 ar2 ar3 ar4 ar5 ar6 ar7 ar8 sar1 wind.reg2 0.7178 0 0 0 0.0780 0 -0.2619 0.1701 -0.2328 26.1504 s.e. 0.0221 0 0 0 0.0255 0 0.0429 0.0367 0.0421 12.9831 sigma^2 estimated as 12.66: log likelihood=-3124.56 AIC=6263.11 AICc=6263.34 BIC=6318.75

The ARIMA model parameters obtained for the SEP time series are presented in Tables 3.43 and 3.44. "ϕ"is related to the AR (Autoregressive), where the order of 1, 5, 7 and 8 are significant and the statistical test value (t-value) is greater than two (critical value). The t-values related to the seasonal autoregressive section within the AR portion is also greater than 2. The inverse of the Spanish electricity generated by the wind coefficient is a significant factor in the SEP.

This result has led the researcher to investigate the role of Spanish wind power generation as an exogenous factor—here introduced as the Xreg Variable in the ARIMA model—for the SEP time series; refer to Chan et al., 2012; Cryer and Chan, 2008; Eriksrud, 2014. However, the residuals analysis of this model indicate there is no valid or suitable ARIMA model for the time series, as there is a large heavy tail in the histogram and Q-Q plot in Figure 3.49. Also, the ACF and PACF of the (squared) residuals show the existence of volatility clustering in Figure 3.50.

Figure 3.51 demonstrates that the large variations in residuals tend to be followed by large changes.

These results point to the suitability of the ARMA-GARCH model for the SEP, as it was for IEP and IEL.

A-Q-Q plot of ARIMA model for SEP time series.	B-Histogram of ARIMA model for SEP time series.

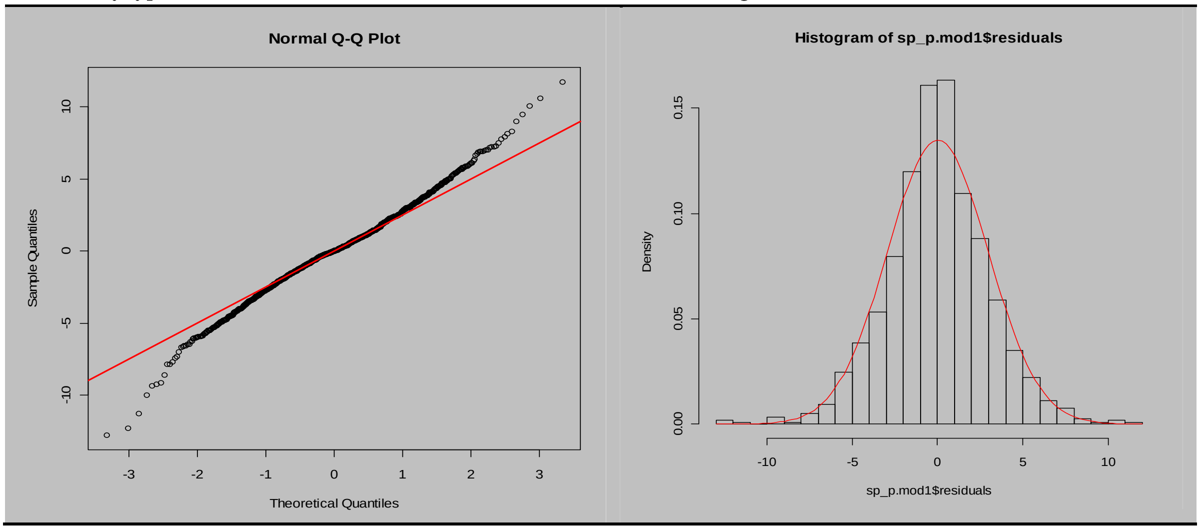


Figure 3.49: Histogram and Q-Q plot;
Residual analysis of the ARIMA model using the SEP histogram and Q-Q plot.

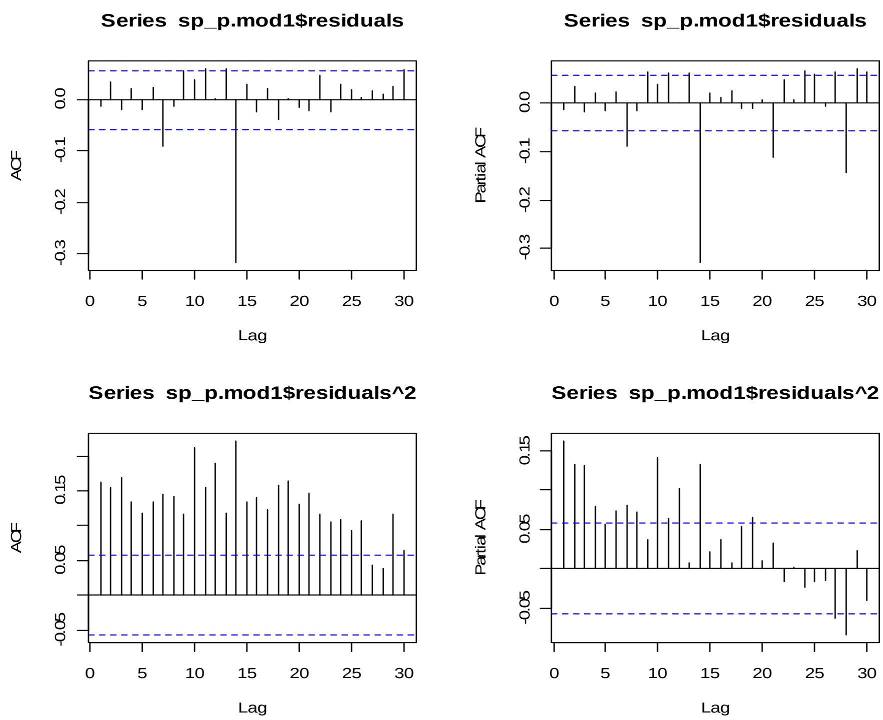


Figure 3.50: The ACF and PACF from the (regular and squared) residuals of the ARIMA model for the SEP time series.

Table 3.44: Statistical equation of the ARIMA model for the SEP time series.

	ARIMA model in statistical equation	MSE
For Spanish electricity price time series	$(1-0.8430B_1 -0.0654B_2)(1+0.4564B_1)^7Yt = e_t + 26.1504wind$	12.57982

Note: the electricity generated by wind power is represented as xreg (here as wind) in this equation.

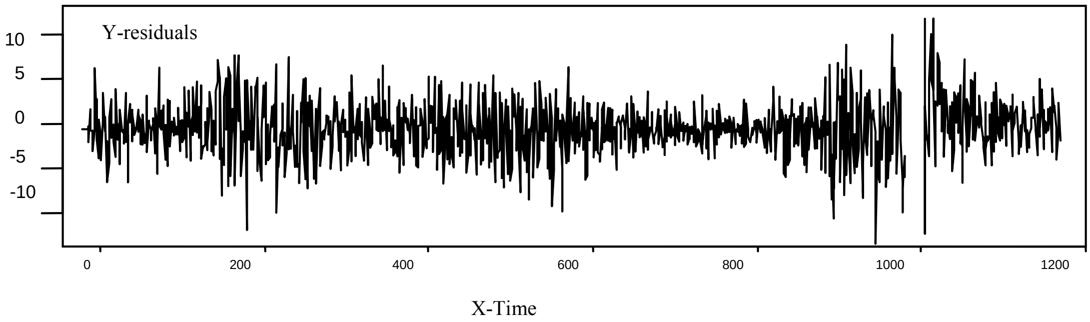


Figure 3.51: The behavior of residuals in the ARIMA model of the SEP time series.

3.3.2.B ARMA-GARCH model

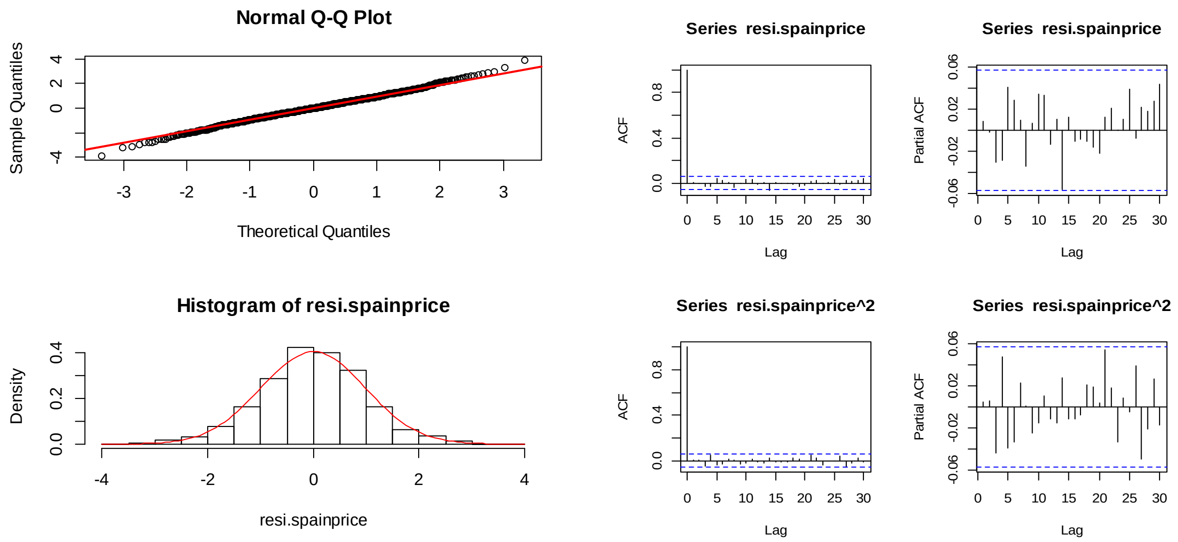
Here, the ARMA-GARCH model was estimated for the SEP (after taking out seasonal differences). The statistical equation of this model is provided in Table 3.44. The residuals do not have a Gaussian distribution in Table 3.47. However, the ACF and PACF, shown in Figure 3.52-B, demonstrate that there is no volatility clustering behavior (serial correlations) in the residuals of this model; also see Figure 3.53.

In addition, the Q-Q plot and histogram show a small heavy tail in Figure 3.52-A. On the other hand, the poly root test function finds no unit roots in the model, because the roots related to the AR section are not equal to one in this ARMA-GARCH model; see Table 3.46 (Pfaff 2008; Box et al. 2013; Prasolov 2009). Therefore, this model can be a good alternative for estimating the price behavior in the Spanish market

Table 3.45: The statistical equation of the ARMA-GARCH model (after taking out seasonal differences).

	ARMA-GARCH model	MSE
For Spain electricity price time series (after taking seasonal difference)	$r_t - 0.566r_{t-1} = a_t - 0.164a_{t-1} - 0.152a_{t-2} - 0.145a_{t-3} - 0.156a_{t-4} - 0.145a_{t-5}$ $- 0.141a_{t-6} + 0.748a_{t-7}$ $a_t = \sigma_t \varepsilon_t$ $\sigma^2 = 0.0391 + 0.0699\varepsilon^2 + 0.92805\sigma^2{}_{t-1}$	0.980117

A- The Q-Q plot and histogram of the residuals. B- The ACF and PACF from the (squared) residuals.



Note: (A) - The Q-Q plot and histogram of the ARMA-GARCH model residuals. (B)- The ACF and PACF of the (regular and squared) residuals of the ARMA-GARCH model.

Figure 3.52: ACF and PACF analysis of the residuals, Q-Q plot and histogram.

Table 3.46: Stationary univariate analysis of the ARMA-GARCH models (after taking out seasonal differences)

R Code(27): Mod(polyroots(1,φ_i))	The poly roots of AR polynomial in the ARMA-GARCH model
Spanish electricity price time series	To estimate the root of AR(1)-Process with φ_1=0.56609: (The roots of AR part): 1.766784

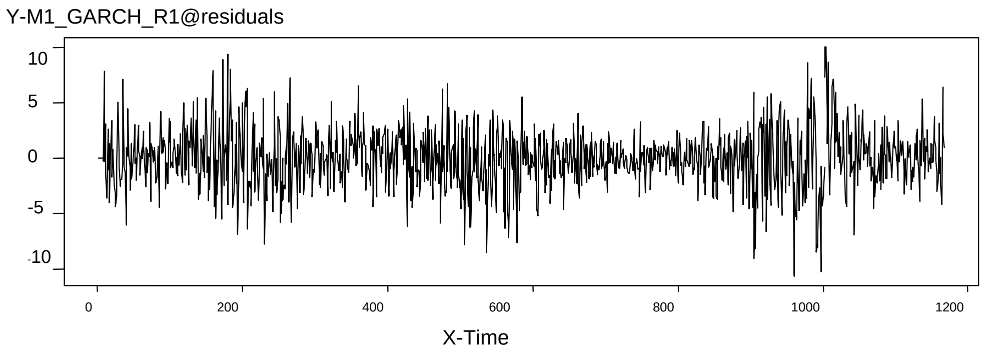


Figure 3.53: The behavior of the ARMA-GARCH residuals model.

Table 3.47: ARMA-GARCH models for the SEP time series
(after taking out seasonal differences).

```
R-code(28):
M1_GARCH_R1=garchFit(~arma(1,7)+garch(1,1),data=d7.spainprice[1:1168],trace=F,cond.dist
="std")
summary(M1_GARCH_R1)
```

```
Coefficient(s):
Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu       0.02970     0.07051    0.421    0.674
ar1      0.56609     0.05107   11.086  < 2e-16 ***
ma1      0.16438     0.03757    4.375 1.21e-05 ***
ma2      0.15253     0.03591    4.247 2.16e-05 ***
ma3      0.14561     0.03414    4.265 2.00e-05 ***
ma4      0.15653     0.03337    4.691 2.72e-06 ***
ma5      0.14545     0.03244    4.484 7.34e-06 ***
ma6      0.14131     0.03163    4.468 7.91e-06 ***
ma7     -0.74835     0.03202  -23.371  < 2e-16 ***
omega    0.03910     0.02127    1.838    0.066 .
alpha1   0.06997     0.01353    5.170 2.34e-07 ***
beta1    0.92805     0.01236   75.088  < 2e-16 ***
shape   10.00000     2.38419    4.194 2.74e-05 ***
Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  12.14413  0.002306407
 Shapiro-Wilk Test  R    W      0.9974741 0.065131
 Ljung-Box Test     R    Q(10)  8.131393  0.6160043
 Ljung-Box Test     R    Q(15)  14.55111  0.4842082
 Ljung-Box Test     R    Q(20)  15.84338  0.726292
 Ljung-Box Test     R^2  Q(10)  9.409371  0.4937426
 Ljung-Box Test     R^2  Q(15)  10.94777  0.7562882
 Ljung-Box Test     R^2  Q(20)  12.58334  0.8945373
 LM Arch Test       R    TR^2   10.53154  0.5694337
```

3.3.2.C SARMA-SGARCH model

As explained in the previous sections, the SEP time series has certain characteristics that cause its behavior to be sector-particular. These features include a seasonal autoregressive component in the conditional mean, heavy tails, and high volatility with a seasonal pattern (Baena and Muñoz, 2013). Table 3.41 clearly indicates the weekly complexity of seasonal unit roots in the behavior of the SEP time series; see Serrano, 2001b. Overall, these conditions and properties have led the researcher to employ SARMA-SGARCH models (Baena & Muñoz, 2013). In comparison to the previous model, the ARMA-GARCH, the seasonal difference is not taken out of the time series for the purpose of estimating the SARIMA-SGARCH model. In other words, the data can be applied directly to the model.

Multiplicative seasonal volatility models (SARMA-SGARCH) are used to estimate the SEP time series, as shown in Tables 3.49 and 3.48. Here, the error distribution follows Gaussian or Student-t distribution. In general, the SARMA-GARCH model function is depicted in Eq. (3.15) and Eq. (3.16):

$$\boldsymbol{\Phi}(\mathbf{B})\boldsymbol{\Phi}_{\mathbf{s}}(\mathbf{B})\mathbf{Y}_{\mathbf{t}} = \boldsymbol{\mu} + \boldsymbol{\Theta}(\mathbf{B})\boldsymbol{\Theta}_{\mathbf{S}}(\mathbf{B})\boldsymbol{\alpha}_{\mathbf{t}} \qquad \text{Eq. 3.15}$$

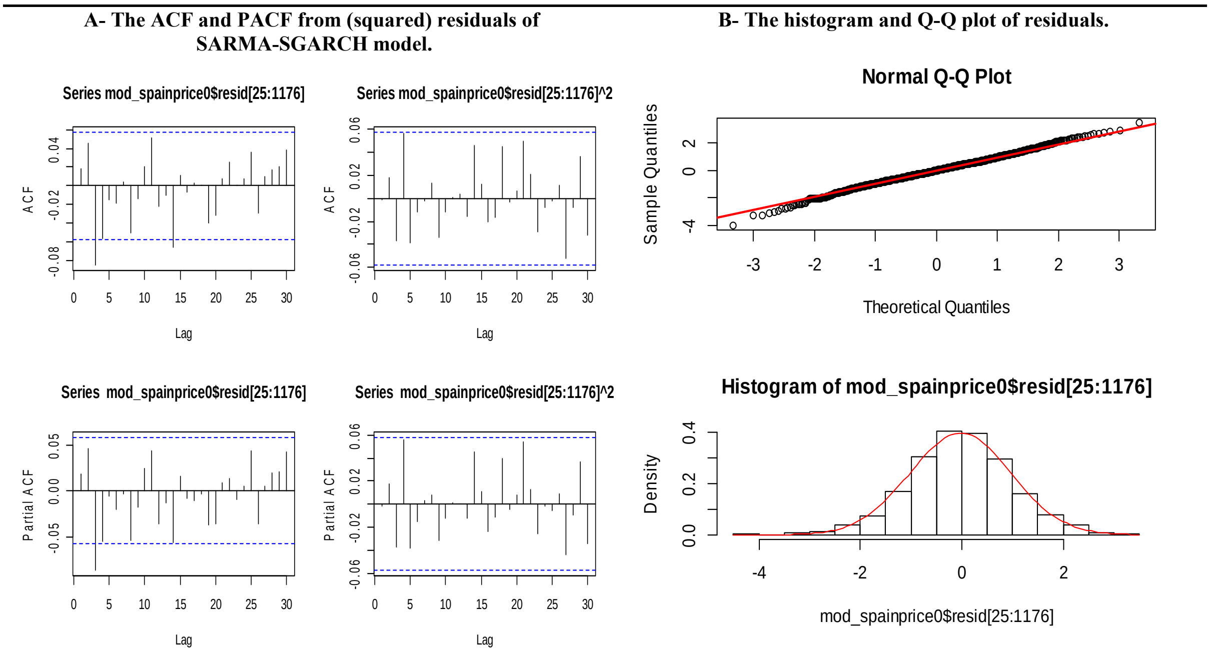
$$\alpha_t = \sigma_t \varepsilon_t$$

$$\boldsymbol{\Omega}_{\mathbf{s}}(\mathbf{B})\boldsymbol{\Omega}(\mathbf{B})\boldsymbol{\sigma}_{\mathbf{t}}^{2} = \mathbf{w} + [\boldsymbol{\Psi}_{\mathbf{s}}(\mathbf{B})\boldsymbol{\Psi}(\mathbf{B}) - \mathbf{1}]\boldsymbol{\alpha}_{\mathbf{t}}^{2} \qquad \text{Eq. 3.16}$$

In Eq. (3.9), the $\Phi(\mathrm{B}) = \sum_{i=1}^{p}(1-\varphi_i \mathrm{B}^{\mathrm{i}})$ and $\Theta(\mathrm{B}) = \sum_{\mathrm{j}=1}^{\mathrm{Q}}(1+\theta_{\mathrm{j}}\mathrm{B}^{\mathrm{j}})$ polynomials are related to the model section without a seasonal autoregressive component in the mean time series. These polynomials are explained through the same reasoning as previously given for the AR section and MA section of the ARIMA model. In the equation above, the polynomials $\Phi_{\mathrm{s}}(\mathrm{B}) = \sum_{i=1}^{p'}(1-\varphi_{s,i}\mathrm{B}^{\mathrm{i-s}})$ and $\Theta_{\mathrm{S}}(\mathrm{B}) = \sum_{\mathrm{j}=1}^{\mathrm{Q}'}(1+\theta_{\mathrm{s,j}}\mathrm{B}^{\mathrm{j-s}})$ are related to the section having a seasonal autoregressive component in the mean time series. All of these four polynomials represent the SARMA section of the SARMA-SGARCH model.

On the other hand, $\Omega(\mathrm{B}) = 1-\sum_{i=1}^{p}\beta_{\mathrm{j}}\mathrm{B}^{\mathrm{j}}\, y$ and $\Psi(\mathrm{B}) = 1+\sum_{\mathrm{j}=1}^{\mathrm{q}}\alpha_{\mathrm{i}}\mathrm{B}^{\mathrm{i}}$ are polynomials related to each section without seasonal conditional heteroscedasticity in the data variance. Polynomials $\Omega_s(\mathrm{B}) = 1-\sum_{i=1}^{p'}\beta_{\mathrm{s,j}}\mathrm{B}^{\mathrm{s-j}}\, y$ and $\Psi_s(\mathrm{B}) = 1+\sum_{\mathrm{j}=1}^{\mathrm{q}'}\alpha_{\mathrm{s,i}}\mathrm{B}^{\mathrm{s-i}}$ cover this type of heteroscedasticity in the variance. These also confirm the SGARCH section of the SARMA-SGARCH model. For further information, see (Baena and Muñoz, 2013; Taylor 2006).

The residuals analysis of the SARMA-SGARCH model demonstrates it to be suitable model. This means an adequate estimation of the behaviour of the SEP time series can be made; see Table 3.48. Figure 3.54-B does not indicate a large heavy tail in the Q-Q plot or histogram of residuals. However, in Table 3.50, the poly-root test uncovers some unit roots in the SAR and AR parts of this model, because the roots are near to one. Therefore, this model may be not a valid model for forecasting the behavior of prices in the Spanish electricity market.



Note: A- ACF and PACF from the (regular and squared) residuals of the SARMA-SGARCH model.

Figure 3.54: Residuals analysis in the ACF and PACF, Q-Q plot and histogram.

Table 3.48: The SARMA-SGARCH model for the SEP time series.

```
R-Code(29):
mod_spainprice0=sarma_sgarch(SEP_new.lin0[1:1176],order=c(1,2),sorder=c(1,2),
period_seasonal=7,gorder=c(1,1),sgorder=c(1,1),period_sseasonal=7,
include.mean=TRUE,tdist=FALSE,s2=NULL)
```

```
> [1] "#####Resultados optimizaciÃ³n#######"
 [1] "Relative gradient is close to zero,
current iterate is probably solution."
[1] "######################"
$ar
              φ1  [,1]
estimate 0.987831931
s.e.     0.005919524
$ma
               θ1 [,1]      θ2  [,2]
estimate -0.26755310 -0.21179123
s.e.      0.03173802  0.03266799
$sar
              Φ7,1  [,1]
estimate 0.984076377
s.e.     0.007253028
$sma
             θ7,1  [,1]     θ7,2  [,2]
estimate -0.9293436 0.02419854
s.e.      0.0341952 0.03373766
$alpha
             α1  [,1]    α2  [,2]
estimate 0.09023410 0.07968083
s.e.     0.08115348 0.02943302
$beta
            β  [,1]
estimate 0.8334994
s.e.     0.1222427
$salpha
             α7,1  [,1]
estimate 0.01899532
s.e.     0.02382089
$sbeta
             B7,1  [,1]
estimate 0.03289690
s.e.     0.04664626
$mean
            µ [,1]
estimate 61.55912
s.e.     16.78751
$Polynomial.SAR Φ7
1 - 0.9878319*x - 0.9840764*x^7 + 0.9721021*x^8
$Roots.Pol.AR (poly root test
[1] 1.012318
$Roots.Pol.SAR
[1] 1.002296 1.002296 1.002296 1.002296 1.002296 1.002296 1.002296
$Polynomial.SMA Θ7
1 - 0.2675531*x - 0.2117912*x^2 - 0.9293436*x^7 + 0.2486488*x^8 +
0.1968268*x^9 + 0.02419854*x^14 - 0.006474393*x^15 - 0.005125038*x^16
$Roots.Pol.MA (poly root test)
[1] 1.631232 2.894519
$Roots.Pol.SMA (poly root test)
 [1] 1.014758 1.014758 1.014758 1.014758 1.014758 1.014758 1.676968 1.014758
 [9] 1.676968 1.676968 1.676968 1.676968 1.676968 1.676968
$Polynomial.SARCH (poly root test)
0.07968083*x + 0.01899532*x^7 + 0.001513563*x^8
$Polynomial.SGARCH Ω7 and ψ7
1 - 0.8334994*x - 0.0328969*x^7 + 0.02741954*x^8
$Roots.Pol.GARCH (poly root test)
[1] 1.199761
$Roots.Pol.SGARCH (poly root test)
[1] 1.628677 1.628677 1.628677 1.628677 1.628677 1.628677 1.628677
```

Table 3.49: The statistical equation of the SARMA-SGARCH model for the SEP time series.

Model	SARMA-SGARCH model	MSE
For Spanish electricity price time series	$(1-0.987B_1)(1+0.9845B_1)^7 Y_t = 61.55 + (1-0.267B_1 - 0.2117B_2)(1\text{-}0.9293B_1\ 0.0241B_2)^7 \alpha_t$ $\alpha_t = \sigma_t \varepsilon_t$ $(1\text{-}0.9023B_1 - 0.0796B_2)(1\text{-}0.0189B_1) = [(1{+}0.833B_1)(1+0.03289B_1)^7 - 1]\alpha_t^2$	1.00194

Table 3.50: Stationary univariate analysis of the SARMA-SGARCH models.

R Code(30): mod(polyroots(1,φ_i))	The poly roots of AR polynomial in the SARMA-SGARCH model
Spanish electricity price time series	To estimate the root of AR(1) -Process with φ_1= 0.987 : 1.012318 To estimate the root of SAR(1) -Process with $\Phi_{7,1}$ =0.984 : 1.002296

3.3.3 Results

3.3.3.A Comparison among of the SEP estimated models.

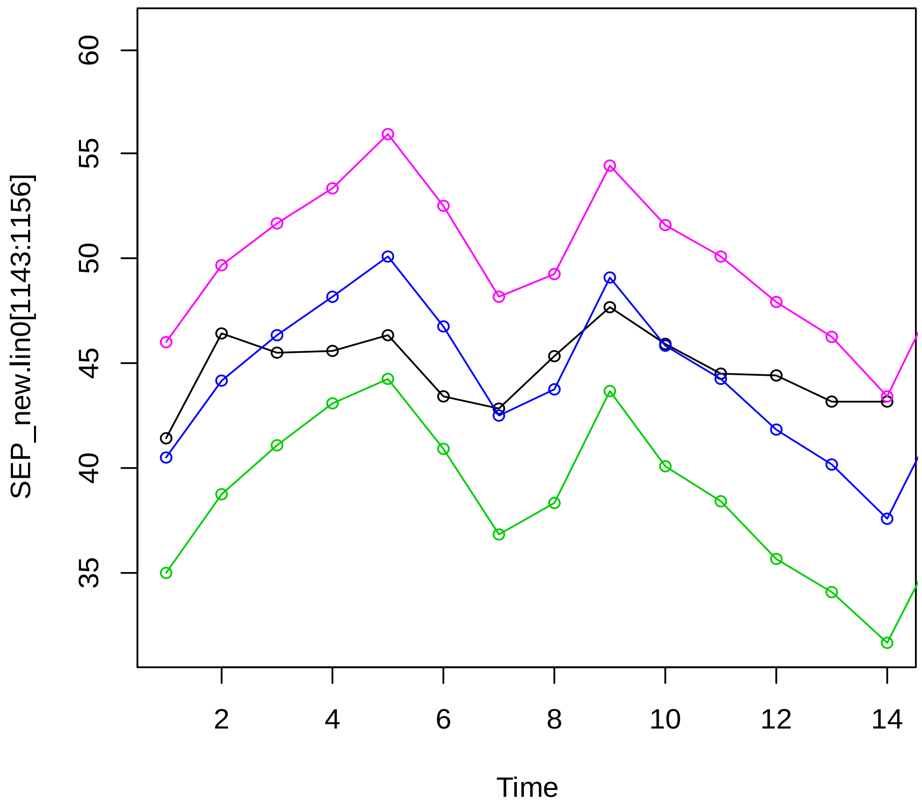
The final results in Table 3.51 abstractly prove that the ARMA-GARCH model and the SARMA-SGARCH model are both valid and suitable models, as there is no volatility clustering in the behavior of the residuals. In contrast with these models, the ARIMA model is not acceptable for estimating the behavior of the SEP time series. This is due to the obvious serial correlations amongst of residuals in this model. On the other hand, the mean square errors in ARMA-GARCH and SARMA-GARCH models are not very different. Overall, the ARMA-GARCH has the lowest error of all other models. Therefore, this model can be accepted as the best one for the research in its attempts to forecast prices in the Spanish electricity market.

Table 3.51: Comparison of the estimated models for the SEP time series.

Time series	Model validation	Residuals validation	Time series in model	MSE
ARIMA model	Not valid	volatility	Spanish electricity price time series	12.57982
ARMA-GARCH model	valid	No volatility No polyroots in AR section of the model	Spanish electricity price (after taking seasonal difference)	0.9801172
SARMA-SGARCH model	valid	No volality Polyroots in AR and SAR section of the model	Spanish electricity price time series	1.001941

3.3.3.B Prediction in sample for Spanish electricity prices

In this section, a prediction in sample was made using the ARMA-GARCH model (see Table 3.45), after taking out seasonal differences from the SEP time series, as shown in Figure 3.55. The sample was taken from the 1143rd to 1156th days. The sample forecast reflected the same behavior, but with real observations. Hence, the results confirm that the model is well-suited for estimating behavior patterns for Spanish electricity prices. An out-of-sample forecast will also be presented in Chapter 4.



Note: Blue points in the figure show the forecast. Black points and lines show the real price. The green and red points and lines show the confidence intervals.

Figure 3.55: In-sample SEP forecast over 14 days (1143th to 1156th) using the ARMA-GARCH model.

3.4 Time series analysis of Spanish electricity loads

In the first part of this section, a data description of the Spanish electricity load (SEL) time series will be given. Based on this analysis, some models will be estimated for the time series. Then a comparison will be, whereupon the best model shall be selected for forecasting the behavior of this time series.

3.4.1 Data description of Spanish electricity loads

The importance of load in electricity market pricing led to the researcher to track the daily SEL time series over the course of three years, as shown in Figure 3.56. The data was calculated daily, in the same way as the SEP time series analysis. In fact, the observation period is equal to that of the SEP time series: 1188 days, starting on July 1, 2007 and ending September 30, 2010. The quantity of the load is based on the "kWh", which is provided for each day. Here, the load time series is divided by 1000 in order to make the scale smaller and simplify calculations.

The daily time series for electricity data in this market is calculated according to "hourly data". The data for the load, provided by Spanish market operator, (2010), are taken daily in order to examine the resulting market behavior using a suitable and valid estimated model. This means a valid load exhibits an indication of the total behavior during a 24-hour period. The programming software "R" was used as the statistical analysis tool (R Development Core Team, 2011a).

The SEL time series in Figure 3.56 demonstrates upward and downward trends in the daily values over these three years. Initially, there are some spikes occurring on special dates in the series, clearly and significantly denoting rather erratic behavior. It could be said that the tendency of the observation variance reverts around a mean level. However, in order to get a suitable estimate from the data, the logarithm as a transformation function is not calculated in the SEL time series. The mean of the Gaussian distribution is not zero; the null hypothesis of the Jarque-Bera test is rejected in Table 3.52. This means that the skewness is not equal to zero and/or the kurtosis is not equal to three in this time series (Pfaff, 2008). The skewness is equal to 0.225 and the kurtosis -0.265, proving that no normal distribution exists—even after detecting the outliers; see Figure 57-A. What is more, the SEL time series histogram in Figure 3.57-B indicates that there is no recognizable distribution in the series.

Table 3.52: Summary of descriptive from daily Spanish electricity load time series.

Statistics	No.obs	Time Span	Median	Min	Max	Mean	Stdev	Skewness	Kurtosis	Jarque-bera Test
Spanish electricity load time series	1188	1/7/2007-30/9/2010	583.28	365.4	826.92	589.11	80.98	0.225 (0.9999)	-0.265 (0.031)	13.4229 (0.001217)

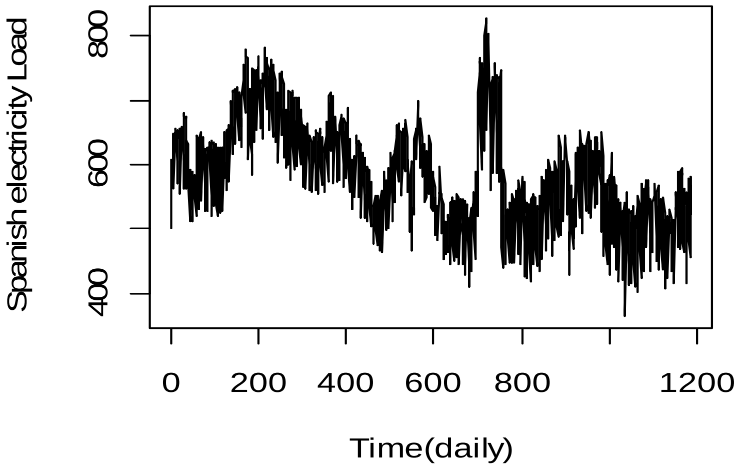
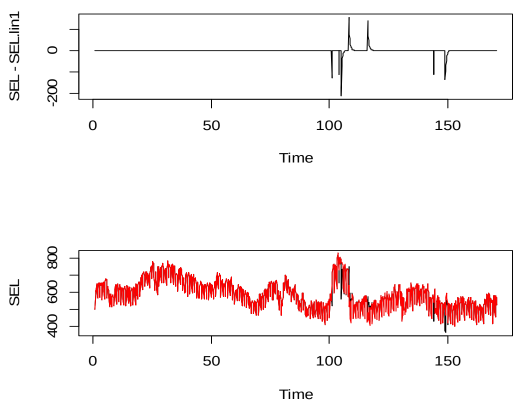


Figure 3.56: Daily SEL time series (2007-2010).

A-Detecting the outliers of daily Spanish electricity load time series (2007-2010).



B- Histogram of daily SEL time series after detecting outliers.

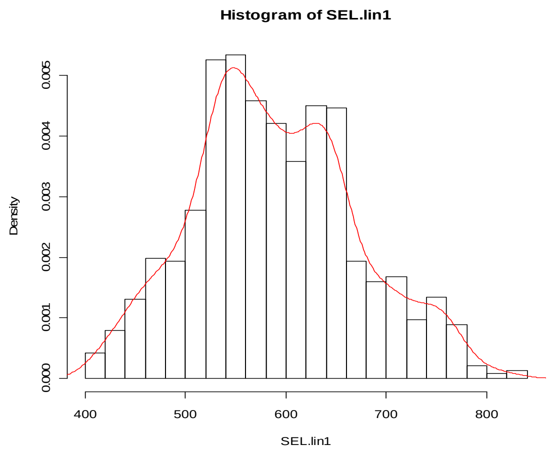


Figure 3.57: Detecting the outliers and histogram of the daily SEL time series.

The SEL time series does demonstrate seasonal behavior in Figure 3.58, as well as a significant decrease in the variance, as seen in Table 3.53, after taking out seasonal differences.

Table 3.53: Variance of Spanish electricity load time series.

Calculate the number of the seasonal difference	1
Variance in Spanish electricity load time series	6650.003
Variance in Spanish electricity load after seasonal difference	1769.004
Variance in the Spanish electricity load (after taking seasonal difference and taking the first order difference)	1032.573

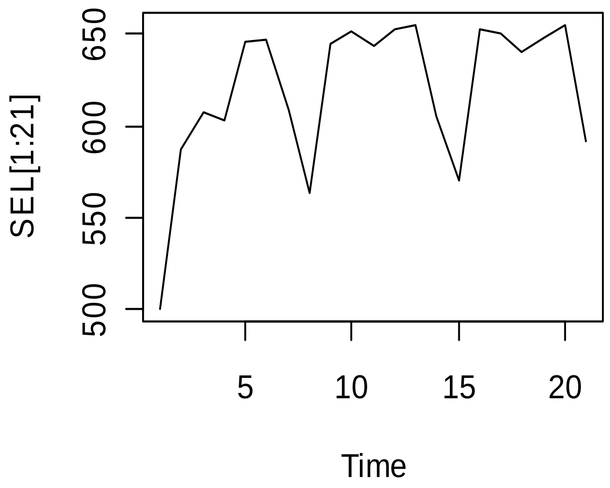


Figure 3.58: 21 days in the SEL time series.

Table 3.54: The Augmented Dickey-Fuller test for Spanish electricity load time series.

Test	For Spanish electricity load time series (After taking seasonal difference)
ADF test	R-cod(31): adf.test(d7.loadspain,k =50) Augmented Dickey-Fuller Test data: d7.loadspain Dickey-Fuller = -5.4632, Lag order = 50, p-value = 0.01 alternative hypothesis: stationary

In this case, the "Augmented Dickey Fuller" (ADF) Test was once again employed, similar to the previous section; see Table 3.54. Next there was an attempt to determine whether the SEL time series is stationary or not (after taking out seasonal differences). As in the other time series, the null hypothesis revealed that the time series is stationary against the alternative that it is not. The p-value derived from the "ADF test" is less than 0.05 (predetermined significance level), proving that the time series is stationary; however, the p-value is greater than 0.05, so the ADF test cannot be utilized, since the SEL demonstrates seasonality as well as cycling behavior over time.

Therefore, the Zivot and Andrews Unit Root Test was used in order to take into account any structural breaks. Here, the null hypothesis is rejected because the test statistics value is less than the critical values at each significance level; see Table 3.55. In conclusion, there is a definite trend occurring in the SEL time series.

Table 3.55: Zivot and Andrews Unit Root Test, after detecting outliers in the SEL time.

Result of Unit root Test	Critical values at 99% confidence interval level	Critical values at 95% confidence interval level	Critical values at 90% confidence interval level
Test statistics value for Spanish electricity load time series:	Critical values		
-8.3939	-5.57	-5.08	-4.82

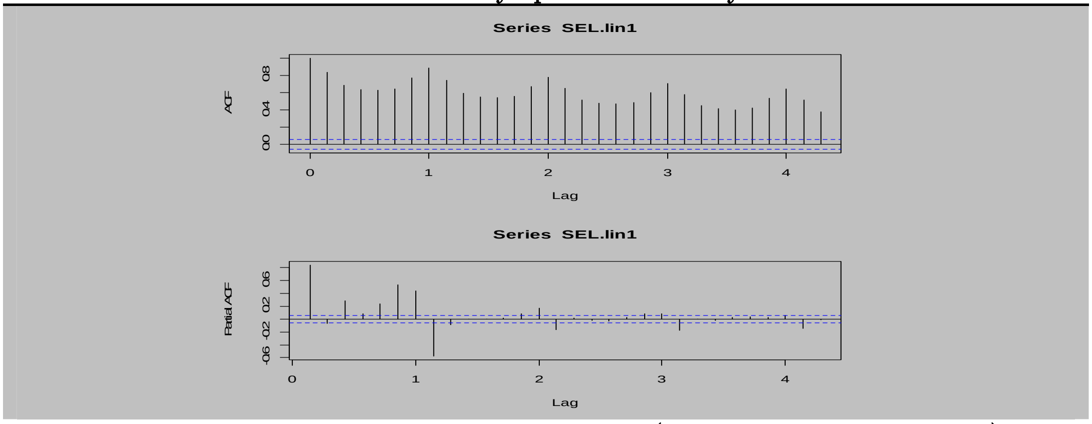
Furthermore, the correlation function (ACF) and autocorrelation function (PACF) show a gradual positive decay over time in Figure 3.60-A. In other words, there is no stationary series because all the lags take place out of the confidence interval levels, even after taking into account seasonal difference; this implies a weak stationary behavior occurring in time series.

Here, there are seasonal cyclical (or a regular cyclical) patterns with peaks occurring every seven units of time; see Figure 3.59. This case also shows the results of the Hegy Test, demonstrating the daily SEL time series (after seasonal difference) has weekly seasonal unit roots; the p-value is less than 0.05 in Table 3.56. Here, according to the non-stationary time series analysis approach, the evaluation of an ARIMA model is attempted in the SEL time series.

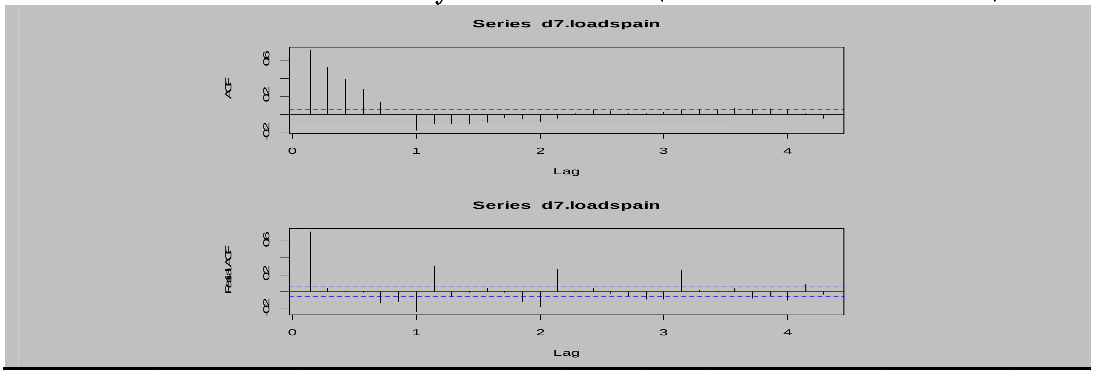
Table 3.56: HEGY test –weekly seasonal unit root test of the SEP time series.

HEGY test results	Null hypothesis : Daily Spanish electricity load time series after first seasonality difference has single unitroots against weekly seasonality unit roots
P-value (The level of the confidence intervals is 95%).	3.10e-07

A- TheACF and PACF of daily Spanish electricity load time series.



B- TheACF and PACF of daily SEL time series (after its seasonal difference).



Note: A- ACF and PACF of the daily SEL time series. **B-** ACF and PACF of the daily SEL time series (after seasonal difference).

Figure 3.59: ACF and PACF of the daily SEL time series.

3.4.2 Spanish electricity load time series modelling

3.4.2.A ARIMA model

As explained above, the non-stationary behavior of the SEL time series has led the researcher to employ the ARIMA model, in order to investigate its behavior in the Spanish electricity market. The model is represented in Table 3.57, while its statistical equation is found in Table 3.58.

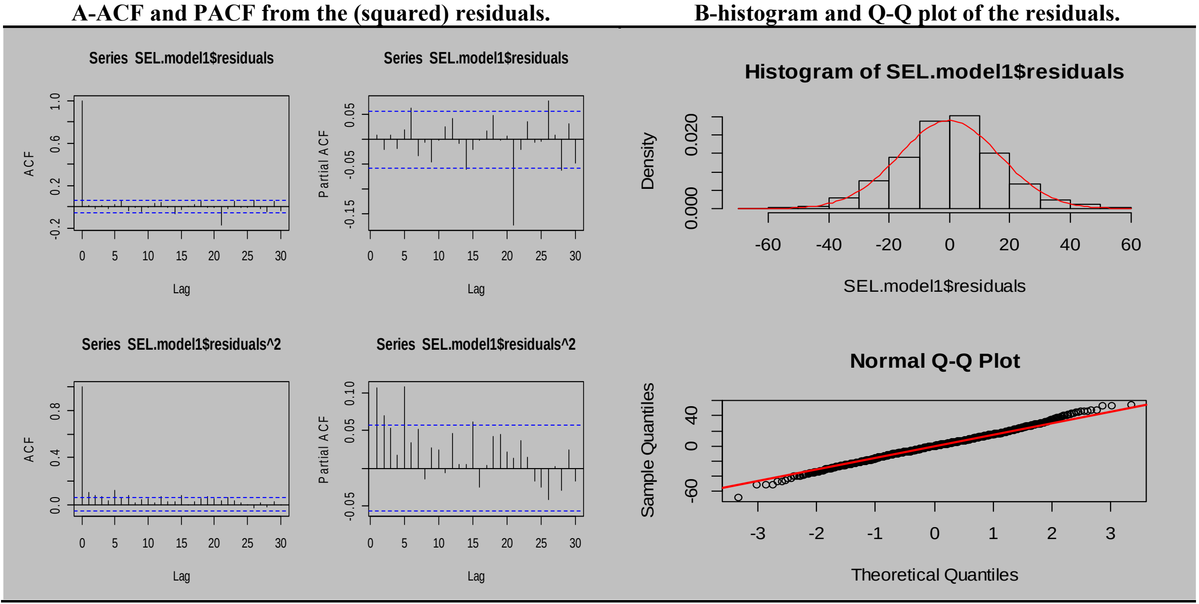
Table 3.57: The ARIMA model for the daily SEL time series.

	R-code(32): **SEL.model1=arima(SEL.lin1[1:1169],order=c(1,0,0),seasonal=list(order=c(2,1,0),period=7))** **SEL.model1**	
Spain electricity load time series	ARIMA (1,0,0) (2,1,0)7	Coeficientes: ar1 sar1 sar2 0.8784 -0.3778 -0.2236 s.e. 0.0144 0.0294 0.0289
		sigma^2 estimated as 278.4: log likelihood = -4920.59, aic = 9849.18

Table 3.58: The statistical equation of the ARIMA model for the SEL time series.

	ARIMA model
Spanish electricity load time series	$(1\text{-}0.8784\ B_1)(1+0.3778B_1+0.2236B_2)^7\ Yt = e_t$

A-ACF and PACF from the (squared) residuals.	**B-histogram and Q-Q plot of the residuals.**



Note: **A**-ACF and PACF from the (squared) residuals of the ARIMA model (for SEL). **B**- Q-Q plot and the histogram of the residuals.

Figure 3.60: Residuals analysis for the ARIMA model (for SEL time series) using ACF and PACF, histogram and Q-Q plot.

In this estimated ARIMA model, the histogram and Q-Q plot show a small heavy tail in Figure 3.60-B. However, it is obvious that there is volatility clustering present in the residuals in Figure 3.60-A and Figure 3.61. The autocorrelation and partial correlation function of the (squared) residuals indicate the cluster (and serial) correlations among of the residuals.

The L-jung Box test also demonstrates the individual non-independence among of the residuals in Figure 3.62 and in Table 3.59. The p-value is greater than 0.05, so the null hypothesis is accepted, and there are serial correlations among of residuals in this model. Thus, due to conditional forecasting and temporal fluctuations in the data-variance, no ARIMA model is capable of accurately modelling such a time series.

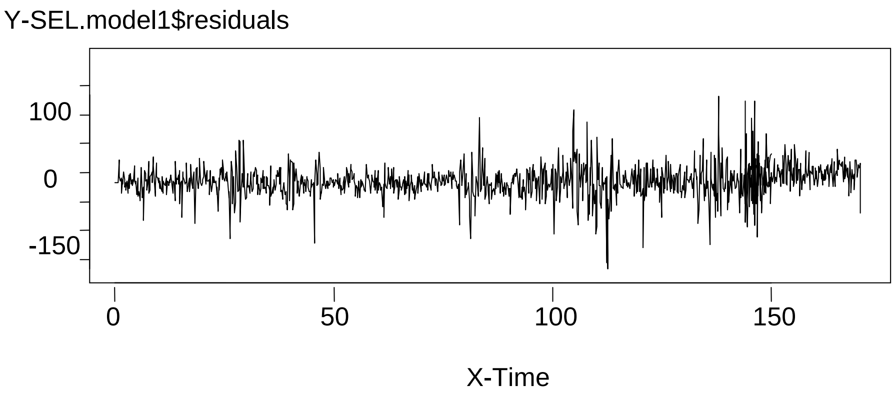


Figure 3.61: Residual behavior of the ARIMA models for the SEL time series.

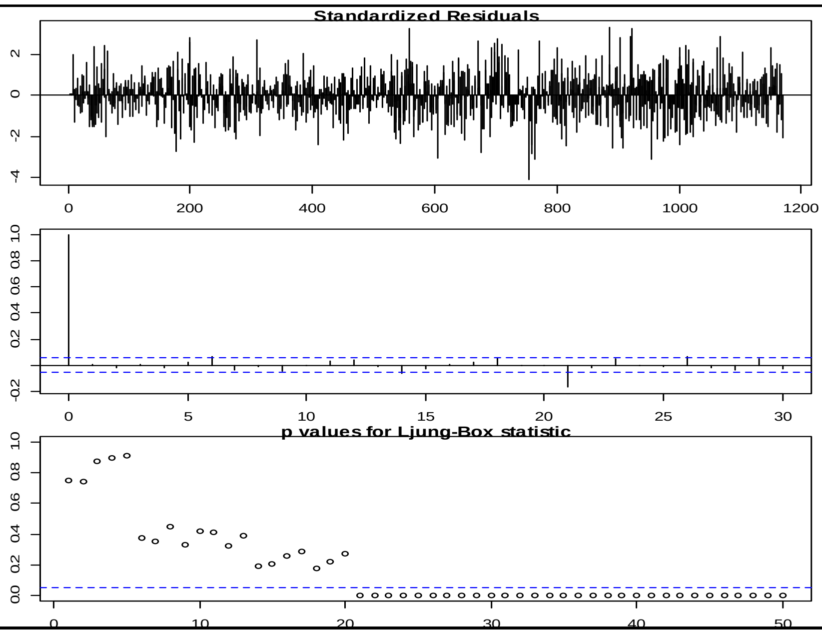


Figure 3.62: L-jung box test of the residuals of the ARIMA model for the SEL time series.

Table 3.59: L-jung box test of the ARIMA model for the SEL time series.

Test	of ARIMA model for Spanish electricity load time series.
Box.test	Box.test(SEL.model1$residuals,lag=10,type="Ljung") Box-Ljung test data: SEL.model1$residuals X-squared = 10.232, df = 10, p-value = 0.4204

3.4.2.B ARMA-GARCH

As previously explained, the residual analysis of the ARIMA models also finds (serial) correlations between the residuals in the SEL time series. In addition, there is a non-constant volatility condition among them(Cryer and Chan, 2008; Tsay, 2005; Wurtz et al., 2006). As discussed in the previous sections, the ARMA-GARCH model in Table 3.60 can be used to investigate and estimate these cluster patterns in the SEL time series (Tsay, 2005).

Table 3.60: Estimated ARMA-GARCH model for the SEL time series. (after taking out seasonal difference).

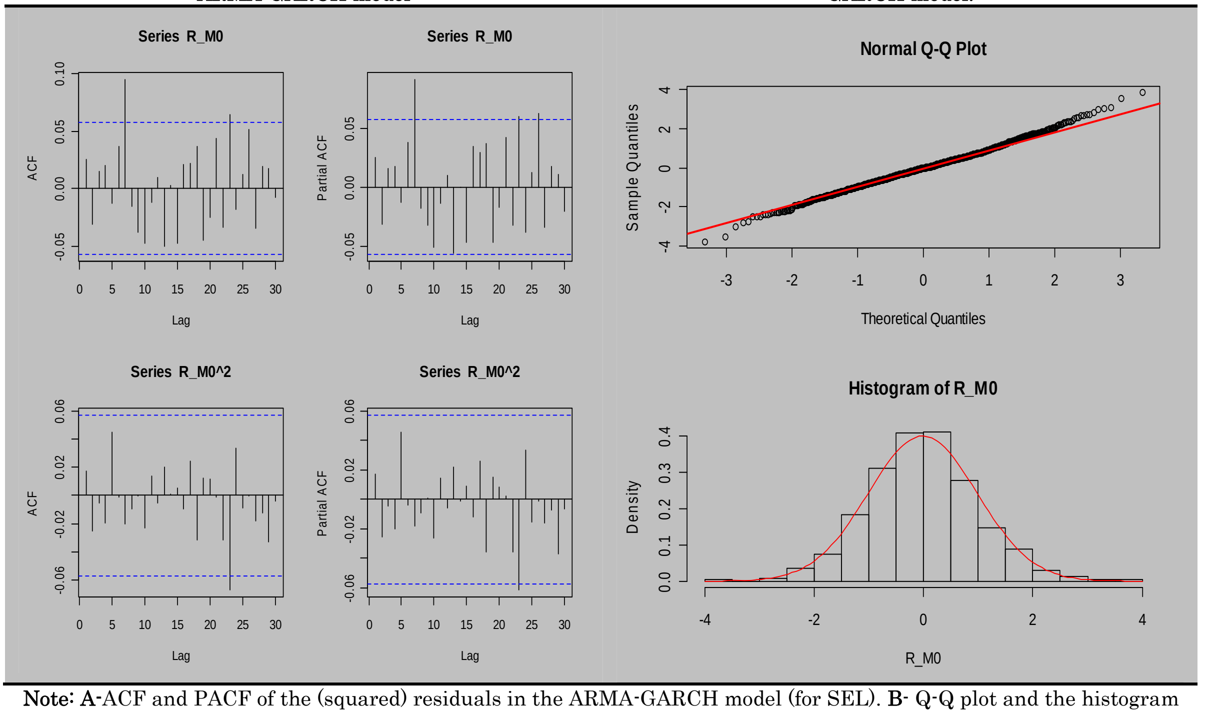
R-code(33):
M1_GARCH_RnSPAI=garchFit(~arma(1,7)+garch(1,1),data=d7.loadspain[1:1168],trace=F,cond.dist ="norm")

```
Coefficient(s):
Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu       0.97938     1.26535    0.774    0.439
ar1      0.41914     0.09009    4.653 3.28e-06 ***
ma1      0.34614     0.07606    4.551 5.33e-06 ***
ma2      0.33354     0.07456    4.474 7.69e-06 ***
ma3      0.33637     0.07352    4.575 4.76e-06 ***
ma4      0.33421     0.07268    4.598 4.26e-06 ***
ma5      0.32493     0.07246    4.484 7.31e-06 ***
ma6      0.32446     0.07131    4.550 5.36e-06 ***
ma7     -0.61841     0.07069   -8.748  < 2e-16 ***
omega   80.26486    14.99553    5.353 8.67e-08 ***
alpha1   0.29313     0.04657    6.295 3.08e-10 ***
beta1    0.57049     0.05597   10.192  < 2e-16 ***
Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  1065.669  0
 Shapiro-Wilk Test  R    W      0.9497288 0
 Ljung-Box Test     R    Q(10)  17.02125  0.07389508
 Ljung-Box Test     R    Q(15)  22.24409  0.1015616
 Ljung-Box Test     R    Q(20)  24.39037  0.2257557
 Ljung-Box Test     R^2  Q(10)  9.802573  0.4579818
 Ljung-Box Test     R^2  Q(15)  12.32375  0.6543766
 Ljung-Box Test     R^2  Q(20)  15.43264  0.7511399
 LM Arch Test       R    TR^2   11.03249  0.5261366
```

Table 3.61: Stationary univariate analysis of the four estimated ARMA-GARCH models.

R Code(34): Mod(polyroots(1,φ_i))	The Poly roots of AR polynomial in the ARMA-GARCH model.
Spanish electricity load time series	To estimate the root of AR(1)-Process with φ_1=0.41914 2.386635

A- The ACF and PACF from (squared) residuals of the ARMA-GARCH model	B- Q-Q plot and the histogram of (residuals) the ARIMA-GARCH model.



Note: **A**-ACF and PACF of the (squared) residuals in the ARMA-GARCH model (for SEL). **B**- Q-Q plot and the histogram of the residuals

Figure 3.63: Residual analysis of the ARMA-GARCH model for the SEL time series via ACF, PACF, Q-Q plot and histogram.

Here, no volatility or a heavy tail was found in Figures 3.63-A and B and 3.64. In addition, the poly-roots test shows that there are no unit roots in the AR section of the model; the root equals more than one. The statistical equation of this model shown in Table 2.62 can be one of the best alternative models in order to estimate the behavior of the SEL time series.

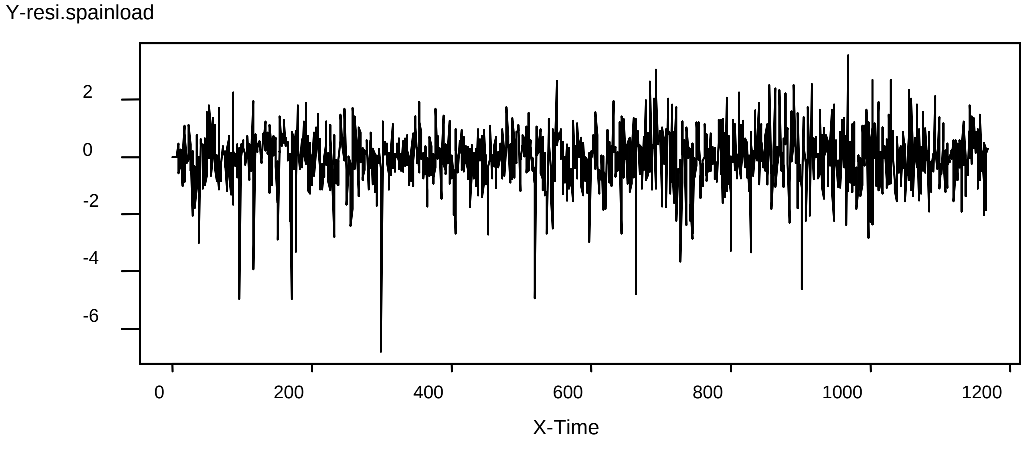


Figure 3.64: Residuals behavior in the ARMA-GARCH model for the SEL time series.

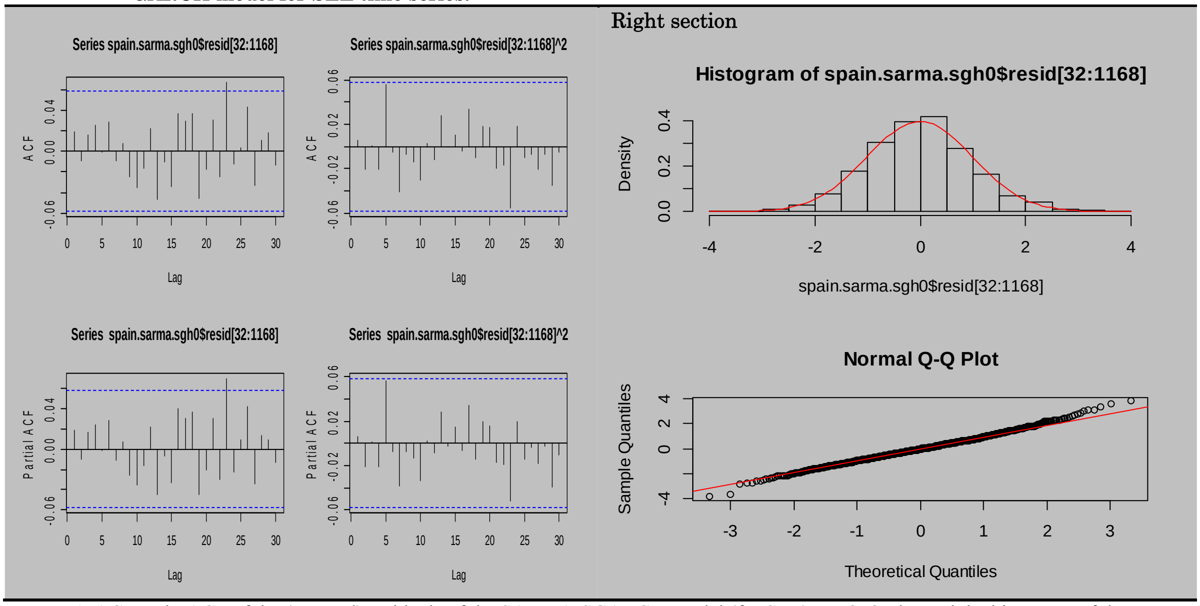
Table 3.62: The statistical equation of the ARMA-GARCH model.

Model	ARMA-GARCH model	MSE
For Spanish electricity load time series (after taking out the seasonal difference time series)	$r_t + 0.4191 r_{t-1} = a_t - 0.346 a_{t-1} - 0.333 a_{t-2} + 0.336 a_{t-3} + 0.333 a_{t-4} + 0.3249 a_{t-5} + 0.3244 a_{t-6} - 0.618 a_{t-7}$ $a_t = \sigma_t \varepsilon_t$ $\sigma^2 = 80.26 + 0.29312 \varepsilon^2 + 0.5704 \sigma^2{}_{t-1}$	0.99634

3.4.2.C SARMA-SGARCH model

The SEL time series, much like the SEP time series, also has some features such as a seasonal autoregressive component in the conditional mean, heavy tails and strong volatility with a seasonal pattern. The weekly complex seasonal unit roots found in Table 3.65 are common in the behavior of the SEL time series. These characteristics again led to the use of the SARMA-SGARCH model for the SEL time series. Here, the seasonal differences are not removed from the time series in estimating the SARIMA-SGARCH model (similar to the SEP time series estimated model). In other words, the data is used directly to provide the model. Thus the multiplicative seasonal volatility models (SARMA-SGARCH) were applied for the SEL time series, as shown in Table 3.63 and Table 3.64.

A-ACF and PACF from (squared) residuals of SARMA-GARCH model for SEL time series.	B-Histogram and Q-Q plot of residuals.



Note: A-ACF and PACF of the (squared) residuals of the SARMA-SGARCH model (for SEL). **B-** Q-Q plot and the histogram of the residuals.

Figure 3.65: Residuals analysis of the SARMA-SGARCH model (for the SEL time series) via ACF, PACF, Q-Q plot and histogram.

Table 3.63: The SARMA-SGARCH model for the SEL time series.

R-code(35):
spain.sarma =sarma_sgarch(SEL.lin1[1:1168],order=c(1,7),sorder=c(1,2),period_seasonal=7, gorder=c(1,1),sgorder=c(0,1),period_seasonal=7,include.mean=TRUE,tdist=FALSE,s2=NULL)

```
$ar
           φ1 [,1]
estimate 0.4420801
s.e.     0.1381504
$ma
         θ1 [,1]     θ2 [,2]   θ3  [,3]   θ4  [,4]   θ5 [,5]    θ6 [,6]
estimate 0.3714727 0.3173273 0.3072898 0.30349480 0.29580337 0.33031304
s.e.     0.1265058 0.1171027 0.1052571 0.09883696 0.09596569 0.09473525
               [,7]
estimate -0.5060436
s.e.      0.1084605
$sar
            φ 7,1 [,1]
estimate 0.997496204
s.e.     0.002737687
$sma
          θ7,1 [,1]     θ7,2 [,2]
estimate 0.07658757 -0.01575197
s.e.     0.04121475  0.03360862
$alpha
           α1 [,1]    α2 [,2]
estimate 13.14870 0.08369774
s.e.      7.24384 0.02379324
$beta
            β [,1]
estimate 0.85599562
s.e.     0.06015617
$salpha
           α7,1 [,1]
estimate 0.008490102
s.e.     0.022019233
$mean
          μ  [,1]
estimate 594.1496
s.e.     193.7971

$ Polynomial.SAR  Φ7
1 - 0.4420801*x - 0.9974962*x^7 + 0.4409733*x^8
$ Roots.Pol.AR
[1] 2.262033
$ Roots.Pol.SAR
[1] 1.000358 1.000358 1.000358 1.000358 1.000358 1.000358 1.000358
$ Polynomial.SMA Θ7
1 + 0.3714727*x + 0.3173273*x^2 + 0.3072898*x^3 + 0.3034948*x^4 + 0.2958034*x^5
+ 0.330313*x^6 - 0.4294561*x^7 + 0.02845019*x^8 + 0.02430333*x^9 +
0.02353458*x^10 + 0.02324393*x^11 + 0.02265486*x^12 + 0.02529787*x^13 -
0.05450862*x^14 - 0.005851425*x^15 - 0.004998529*x^16 - 0.004840418*x^17 -
0.00478064*x^18 - 0.004659485*x^19 - 0.00520308*x^20 + 0.007971182*x^21
$ Roots.Pol.MA
[1] 1.043816 1.021077 1.032414 1.043816 1.032414 1.021077 1.632072
$ Roots.Pol.SMA
 [1] 1.404137 1.288588 1.288588 1.288588 1.288588 1.288588 1.288588 1.404137
 [9] 1.404137 1.404137 1.404137 1.288588 1.404137 1.404137
$ Polynomial.SARCH
0.08369774*x + 0.008490102*x^7 + 0.0007106024*x^8
$ Polynomial.GARCH  Ω7 and ψ7
1 - 0.8559956*x
$Roots.Pol.GARCH
[1] 1.16823
```

Table 3.64: The statistical equation of the SARMA-SGARCH model (for the daily SEL time series).

	SARMA-SGARCH model	MSE
For the Spanish electricity load time series	$(1-0.442B_1)(1-0.9974B_1)^7Y =_t 594.14 + (1+0.371B_1+0.3173B_2+0.3072B_3 + 0.3034B_4+0.2958B_5+0.3303B_6-0.506B_7)\alpha_t$ $\alpha_t = \sigma_t\varepsilon_t$ $(1-0.083B_2)\sigma_t^2 = [(1+0.855B_1)-1]\alpha_t^2$	1.007376

Although no volatility behavior was found among the residuals in Figure 3.65-A and B, this model cannot be a suitable model for the SEL time series according to Table 3.65, because there are unit roots in the SAR section of the model.

Table 3.65: Stationary univariate analysis of the SARMA-SGARCH models.

R Code(36): mod(polyroots(1,φ_i)) For	The estimation mod of Poly roots test for AR Sections of each SARMA-SGARCH model
Spanish electricity load time series	Estimation of AR(1)-Process with φ_1= 0.442: 2.262033 Estimation of SAR (1)-Process with $\varphi_{7,1}$ =0. 0.997 : 1.000358

3.4.3 Results

3.4.3.A Comparison of the SEL estimated models

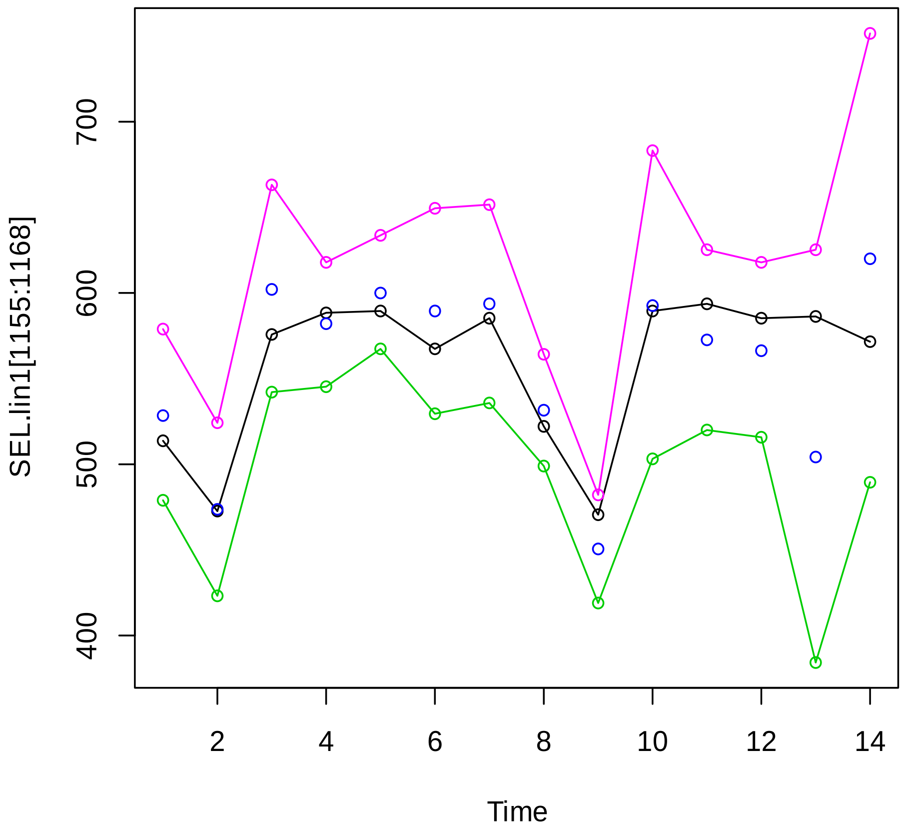
As shown in Table 3.66, the ARMA-GARCH model seems to be the best model for predicting load behavior patterns in the Spanish electricity market in this study. Other models, such as the ARIMA model, did not perform a suitable forecast, mainly due to the volatility of the residuals. On the other hand, the SARMA-SGARCH model cannot be considered an accurate model either, because of the existence of unit roots, in comparison with the ARMA-GARCH model. In addition, the mean square error of the ARMA-GARCH model is less than the other models. Therefore, this model has been chosen as the best to forecast the Spanish electricity load in the future.

Table 3.66: Comparison of the estimated models for the SEL time series.

Models	Model validation	Residuals validation	Time series in model	MSE
ARIMA model	Not valid	volatility	Spanish electricity load time series	735.0407
ARMA-GARCH model	valid	No volatility no unitroots	Spanish electricity load after taking seasonal difference	0.9963485
SARMA-SGARCH model	Low valid	Unitroots	Spanish electricity load time series	1.007376

3.4.3.B Prediction in sample of Spanish electricity loads

In this case, similar to that of the other time series, a daily forecast in sample was made for SEL time series, as shown in Figure 3.66. It is clear that most of the prediction points are within the confidence intervals. The forecast is based on the best model, the ARMA-GARCH in Table 3.62. The daily forecast in sample was performed from the 1155th to 1168th days. The sample forecast has very similar behavior to the real observation. An out-of-sample forecast of the SEL will be provided in Chapter 4.



Note: Blue points in our figure show the forecast. **Black points and lines** show the real load. **Green and blue points and lines** show the confidence intervals.

Figure 3.66: SEL forecast in sample for 14 days (1155th to 1168th) using the ARMA-GARCH model.

3.5 The impact of load on the price of electricity

In this section, the research shall turn to the relationship between the two main factors/indices—load and price—within each electricity market separately. From the conclusions reached in Sections 3.1 and 3.2, it was decided that the best and most valid model for the Iranian electricity price time series was the non-linear ARMA-TGARCH model. The autoregressive conditional heteroscedasticity model (ARMA-GARCH) was selected for the Iranian electricity load time series in this study.

Both models displayed significantly different behavior within their respective time series. Such results have led the researcher to investigate the impact of load on prices in this market, as compared to the Spanish electricity market. Afterwards, an evaluation has been made as to whether a relationship exists between these important factors in the Iranian electricity market. To do this, statistical time series analysis methods (such as scatter plots, etc.) will be used to determine the impact of load on electricity prices in both the Iranian and Spanish electricity markets, as shown in following.

3.5.1 Scatter plots

In order to prove the relationship between the time series in their respective markets, "scatter plots" have been used to visually display any potential correlation. A scatter plot is a type of graph that shows the data of two variates plotted along its axes. The points are positioned so as to indicate the value of these variates in each subject. The upshot is that the form of the association between the variates can easily be seen. Of all the graphic forms used today, the scatter plot is the most discussible, versatile, polymorphic, and generally usable invention in the history of statistical graphics. Its use by Galton led to the discovery of correlation and regression, and ultimately to much of present multivariate statistics (Friendly & Denis 2005). "The scatter plot is an easy-to-see method of revealing obvious relationships between two variables. In this thesis, the scatter plot is used to evaluate the type of relationship existing between each of our time series in both markets."

"Normally, for pairs of value variables, the x-axis indicates the independent variable and the y-axis the dependent variable (Sharma, 2008). Patterns in the relationship between the pairs are represented by a straight line. If the variables are related, then a dotted line appears in each diagram and describes the relationship between the two variables"(Sharma 2008).

A straight line indicates the direction of the correlation between the variables; a negative or positive correlation, or no correlation. Figure 3.67 displays the pattern of the relationship between the value pairs of the electricity indices (the IEP and IEL time series). This scatter plot displays no line whatsoever between the daily Iranian electricity loads and prices, and nor does the graph show any slope, positive or negative. What is more, even after decreasing the non-stationary behavior—by the taking out the first-order difference from the IEP time series and the seasonal and first-order differences from the IEL time series—in Figure 3.67-B, there is still no clear positive or negative correlation between these two time series (in this case, the IEP time series is introduced as the dependent variable on the scatter plot and IEL as the independent variable).

A-Scatter plot of Iranian price and load time series.	B-Scatter plot of Iranian price and load time series (After taking their difference).

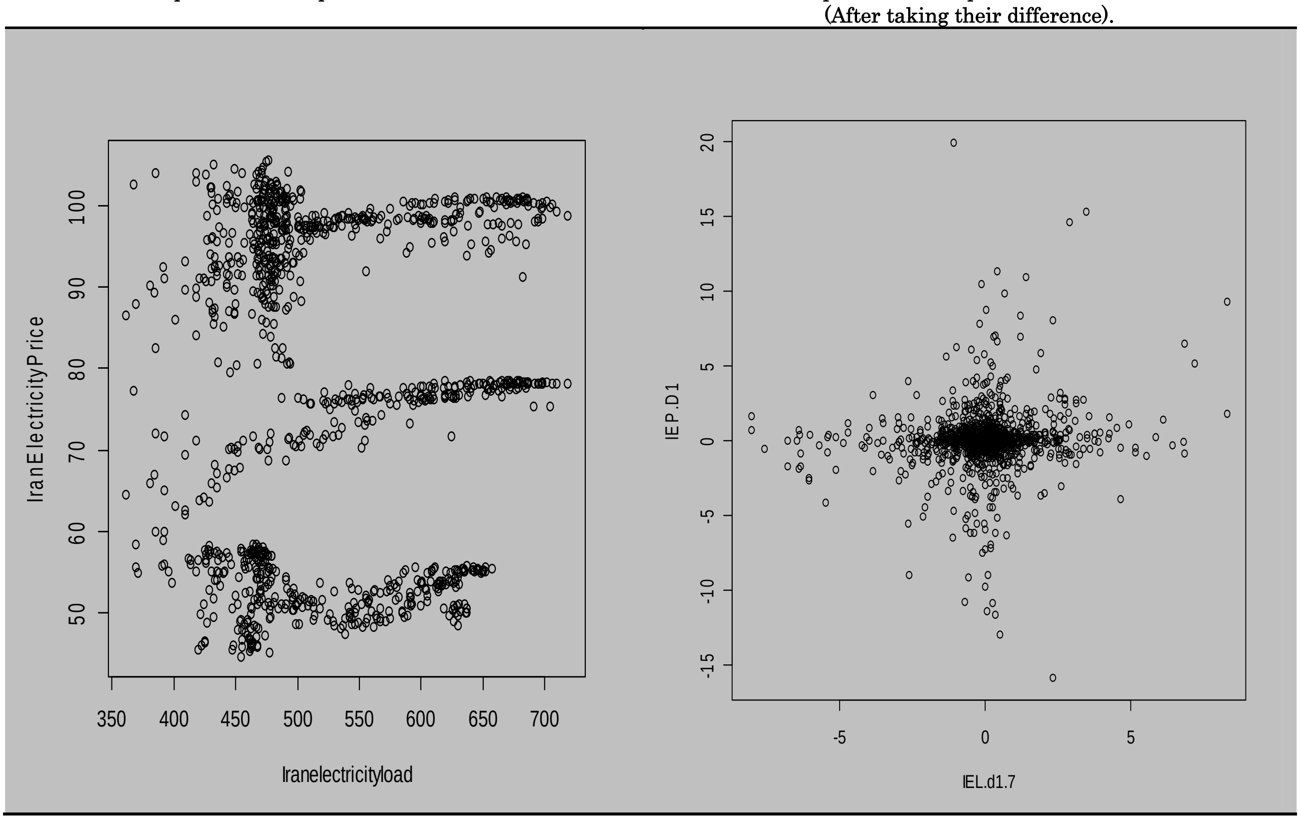


Figure 3.67: Scatter plots indicating the correlation between the daily IEP and IEL time series.

For the daily SEL and SEP time series, the same type of model was estimated, the autoregressive conditional heteroscedasticity or ARMA-GARCH model. This result leads the researcher to the conclusion that both time series exhibit the same behavioral patterns over time.

In contrasting with the Iranian electricity market, the Spanish market has a positive correlation is some areas of the SEP and SEL time series; see Figure 3.68. Such a result is not surprising, given the effect of wind power generation on the price behavior patterns in the Spanish market (Ketterer, 2014).

Other plots were generated using the R code command lag2.plot (spainload, spainprice, max.lag=10), which are shown in Figure 3.69.

R-CODE(37):

```
lag2.plot (spainload, spainprice, max.lag=10)
```

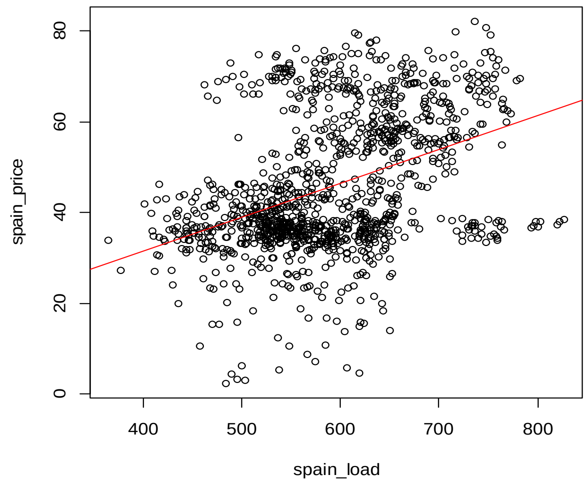


Figure 3.68: Scatter plot displaying the correlation between the daily SEP and SEL time series.

In these plots, the SEP time series (as the dependent variable) is on the vertical axis while a previous lag of the SEL time series (as independent variable) is on the horizontal axis. Here, the correlation values also are given on each plot (see PennState, 2014). These plots display certain relationships between the SEP and SEL time series even at a previous lag of the SEL equal to 7. Their cross-correlation will be needed in order to clarify these results.

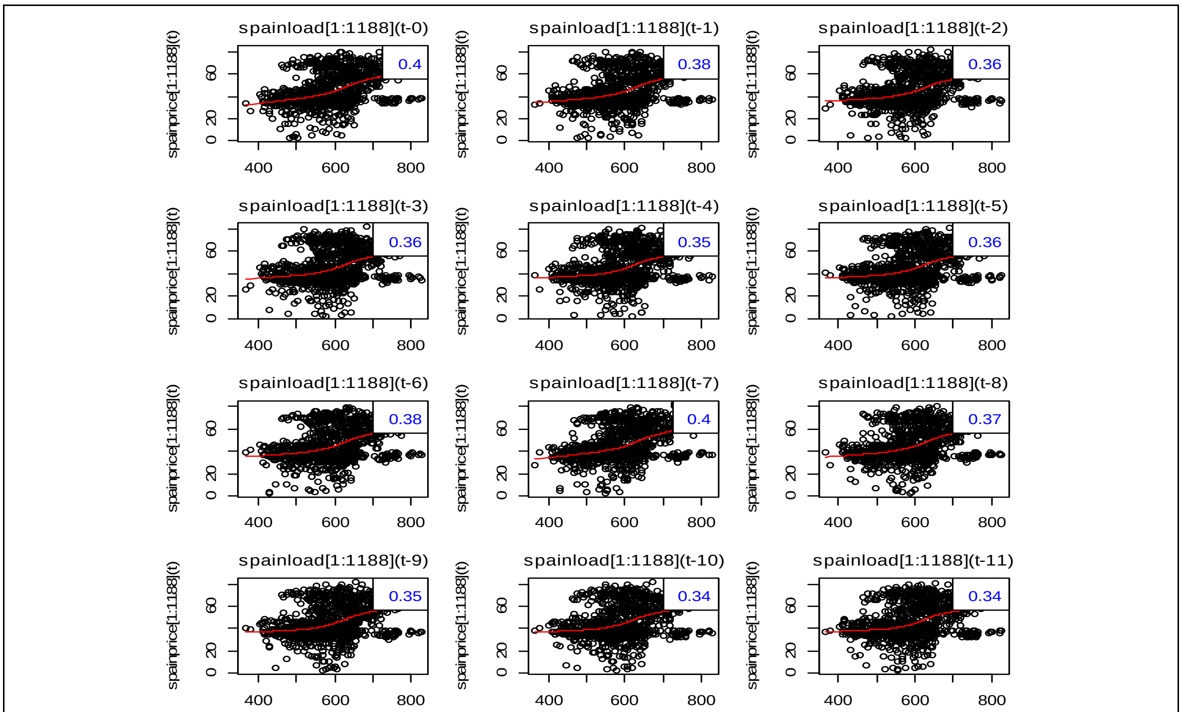


Figure 3.69: Scatter plot of the SEP versus the SEL time series at each lag.

3.5.2 Cross correlation function

The scatter plots indicate the lack of a linear relationship between the IEP and IEL time series. However, it may be that their correlation (the IEP as y_t or the dependent variable, and the IEL as x_t, the independent variable) is due to previous lags in the x-series (PennState, 2014). The cross correlation function (CCF) is useful for identifying the kind of relationship existing between two (or more) stationary time series over time. In general, the sample cross-correlation between two time series is (Eq 3.17):

$$r_{xy}(k) = c_{xy}(k)/\sqrt{[c_{xx}(0)c_{yy}(0)]}$$

Eq 3.17

Supposing there are N pairs of observations $\{(x_t, y_t), t=1,\ldots,n\}$ on two time series. Here, after decreasing the non-stationary behavior in the time series, this function is calculated. These estimations used the IEP time series after taking out first-order differences $\{\nabla(1-B)y_t\}$ and the IEL time series after taking out seasonal differences $\{\nabla((1-B)(1-B^7))X_t\}$. The coefficient, for lag k, namely $C_{xy}(k)$, provides an estimation of the population cross covariance coefficient between the two time series (for more information, see Chatfield 2013).

In other words, this sample cross correlation function (CCF) is helpful for identifying lags in the x-variable that might be useful predictors of y_t" (PennState, 2014), where $C_{xx}(0)$ and $C_{yy}(0)$ are the variance of the load (x) and price (y) (Chatfield 2013).

In Figure 3.70 and Table 3.67, the $\nabla((1-B)(1-B^7))Load_{t+h}$ are very weak predictors of the $\nabla(1-B)Price_t$ because the cross correlation values up to lag=7 are mostly insignificant at the 90% confidence interval level. This means the load does not both lead and lag at the price used in the Iranian electricity market; see also Figure 3.67. For instance, consider $h= -2$, the CCF value would give the correlation between $\nabla((1-B)(1-B^7)Load_{t+h}$ and $\nabla(1-B)price_t$.When one or more x_{t+h}, with k negative, are predictors of y_t, it is sometimes said that x leads y. When one or more x_{t+h}, with h positive, are predictors of y_t, it is sometimes said that x lags y. (see PennState (2014)).

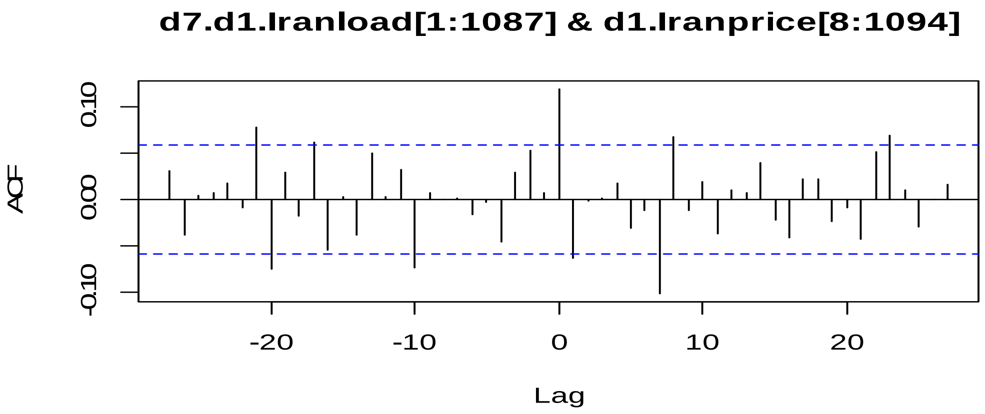


Figure 3.70: Cross-correlation functions from the SEP and SEL time series.

Rcod(37): Cross correlation function diagram for Iranian electricity price time series and Iranian electricity load time series.

```
ccf(d7.d1.Iranload[1:1087],d1.Iranprice[8:1094])
```

Table 3.67: Cross-correlation values in each lag in the IEP and IEL time series.

```
R code(38): d7.d1.Iranload[1:1087],d1.Iranprice[8:1094])
                              Autocorrelations of series 'X', by lag

   -27    -26    -25    -24    -23    -22    -21    -20    -19    -18    -17
 0.031 -0.038  0.004  0.008  0.017 -0.008  0.078 -0.076  0.030 -0.018  0.062
   -16    -15    -14    -13    -12    -11    -10     -9     -8     -7     -6
-0.055  0.003 -0.038  0.050  0.004  0.033 -0.074  0.007  0.000  0.001 -0.016
    -5     -4     -3     -2     -1      0      1      2      3      4      5
-0.004 -0.045  0.029  0.054  0.008  0.119 -0.063 -0.002  0.001  0.017 -0.031
     6      7      8      9     10     11     12     13     14     15     16
-0.011 -0.102  0.068 -0.012  0.020 -0.038  0.010  0.007  0.040 -0.022 -0.042
    17     18     19     20     21     22     23     24     25     26     27
 0.022  0.022 -0.024 -0.009 -0.043  0.052  0.069  0.011 -0.029  0.000  0.016
```

Overall, these results give rise to examining the possibility of estimating the dynamic regression model for the Iranian electricity market time series (See next section). This idea will be explored by estimating the time series behavior using the Rational Distributed Lag Models (Pankratz, 2012), a type of estimation models used in dynamic linear time series (see Pankratz, 2012 and the next section of the thesis).

Conversely, the cross correlation function displays weak correlation within the SEL and SEP time series. This function is calculated according to both indices: the SEL time series—after taking out the seasonal and first-order difference $\{\nabla(1\text{-}B)(1\text{-}B)^7 x_{t+k}\}$—and the SEP time series—after taking out the first-order difference $\{\nabla(1\text{-}B)y_t\}$. Here, there is a clearly negative correlation between the two at lag=5 and a positive correlation at lag=2, as shown in Figure 3.71 and Table 3.68. So, here also, when one or more x_{t+k}, with k negative, are predictors of y_t, it is sometimes said that x leads y. When one or more x_{t+k}, with k positive, are predictors of y_t, it is sometimes said that x lags y. (see PennState, 2014).

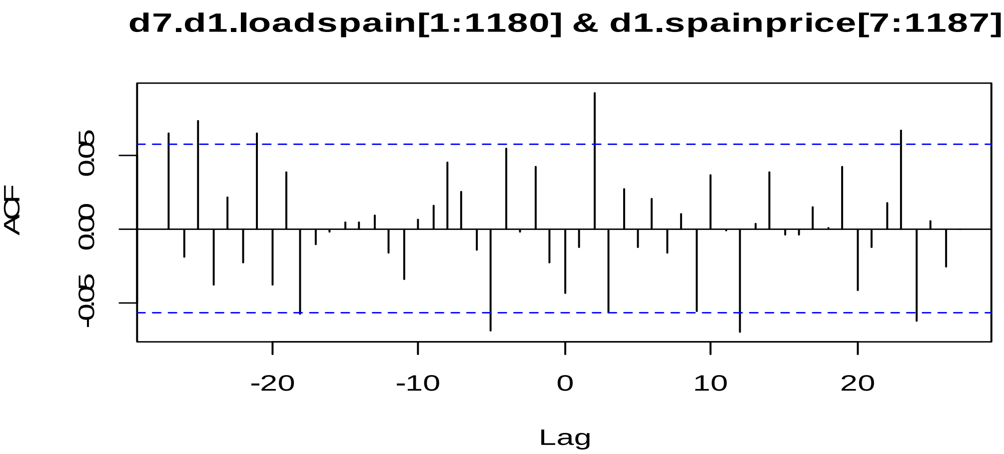


Figure 3.71: Cross-correlation function of the Spanish electricity market time series.

Table 3.68: Cross-correlation values from Spanish price and load time series.

```
R-code(39): ccfvalues = ccf(d7.d1.loadspain[1:1180],d1.spainprice[8:1094])
ccfvalues
```

```
Autocorrelations of series 'X', by lag

   -27    -26    -25    -24    -23    -22    -21    -20    -19    -18    -17
-0.130  0.070 -0.019  0.075 -0.039  0.016 -0.021  0.068 -0.044  0.044 -0.057
   -16    -15    -14    -13    -12    -11    -10     -9     -8     -7     -6
-0.012  0.000  0.004  0.005  0.009 -0.018 -0.037  0.008  0.020  0.046  0.024
    -5     -4     -3     -2     -1      0      1      2      3      4      5
-0.015 -0.072  0.058 -0.007  0.045 -0.024 -0.046 -0.004  0.087 -0.058  0.031
     6      7      8      9     10     11     12     13     14     15     16
-0.020  0.019 -0.020  0.014 -0.055  0.042 -0.014 -0.068  0.007  0.048 -0.010
    17     18     19     20     21     22     23     24     25     26     27
-0.012  0.021  0.005  0.042 -0.046 -0.010  0.021  0.064 -0.056  0.003 -0.027
```

For the Spanish electricity time series, there also is the option of estimating the dynamic regression model, "the Rational Distributed Lag Model". To do so, in the next section the SEP is used as the dependent (output) variable, while SEL is the independent (input) variable. This model is used to clarify the existence of a relationship between these indices according to the model used for the Spanish electricity market (see next section).

3.5.3 Rational Distributed Lag Model (with SAS)

The ARIMA Regression model for the disturbance is determined to be a dynamic regression, since Y_t depends on the past disturbance value, although a dynamic regression might also involve past input values. Hence, it seems that the ARIMA could not be responsible for these issues, so they are not included in the time lagged X's in the regression. This is why regression models with time lagged inputs are also called distributed lag models Eq. (3.18). Here, the focus is on a certain parsimonious form called the rational distributed lag form (or "KoycK model") (see Pankratz, 2012).

The parsimonious form of the "KoycK model" (or ARIMAX model) in Eq. (3.18) is used to investigate the impact of load—as the input value over time—on price—as the output value over time, for more detail information see (Pankratz, 2012). If the input series is auto-correlated, the direct cross-correlation function between the input and response series should give a misleading indication of the relationship between the input and response series. One way of solving this problem is called pre-whitening, which means fitting an ARIMA model to the input series that is adequate for reducing the residuals to white noise. Then, the input series must be filtered through this model to obtain the white noise residual series. After that, the response series has to be re-filtered through the same model and the resulting response cross-correlated with the filtered input series (Pankratz, 2012).

The result of this time series modelling approach for the SEP is shown in Tables 3.69 and 3.70. The impact of the wind power generation was added, because as it was explained in Section 3.3, wind power also influences the behavior patterns of the SEP (all calculations related to this model are presented in Appendix A).

The ARIMAX model was estimated by the SAS programming software (Institute SASInc., 2008). In this model, the daily SEP was estimated as output, load and the wind power as the inputs, and the mean term defined as μ= 0. As it can be observed in Table 3.70, the SEL time series has an impact on market prices at time ¨t¨. What is more, the coefficients are significant in the estimated model.

$$W_t = \mu + \sum_i \frac{\omega_i(B)}{\delta_i(B)} B^{ki} X_{i,t} + \frac{\theta(B)}{\phi(B)} a_t \qquad \text{Eq. 3.18}$$

Where

t time indices

$X_{i,t}$ input time series or difference of the ith input series at time t.

K_i pure time delay affecting the ith input series

$\omega_i(B)$ polynomial numerator of the transfer function in the ith input series

$\delta_{i(B)}$ polynomial denominator of the transfer function in the ith input series

w_t response series Y_t or a difference series

μ mean term

ϕ (B) , autoregressive operator, represented as a polynomial in the back shift operator; operator $\phi(B)=1+ \phi_1 B- \ldots\ldots+\phi_p B^p$

θ(B) , moving average operator, represented as a polynomial in the back shift operator; operator $\theta(B)=1- \theta_1 B- \ldots\ldots -\theta_q B^q$

where $\phi(B)=1+ \phi_1 B- \ldots\ldots+\phi_p B^p$ and $\theta(B)=1- \theta_1 B- \ldots\ldots -\theta_q B^q$ notice how the AR coefficients get mixed up with both the covariates and the error term.

a_t independent disturbance, also called the random error (Stage & Statements,2013).

Table 3.69: The statistical equation of the ARIMAX model for the daily SEP/SEL time series.

Model	Statistical equation of the Rational Distributed Lag Model
For Spanish electricity price time series (as dependent variable(output)) and Spanish electricity load time series (as independent variable(input))	$pr_t = \frac{(0.4282 + 0.1189 B^1)}{(1 + 0.6499 B^1)} Load_t + (0.1404 + 0.01404 B^7) wind_t + \frac{(1 - 0.975 B^1)}{(1 + 0.2819 B^1 + 0.24977 B^2 + 0.1994 B^3 + 0.0822 B^4)} \alpha_t$

Table 3.70: Rational Distributed Lag Model (ARIMAX) for the SEP time series.

ARIMAX Model for variable price

Period(s) of Differencing 1,7
No mean term in this model.
Autoregressive Factors
Factor 1: 1 + 0.28191 B**(1) + 0.24977 B**(2) + 0.19447 B**(3) + 0.08224 B**(4)
Moving Average Factors
Factor 1: 1 - 0.97533 B**(7)

Input Variable 1 load

Period(s) of Differencing 1,7
Numerator Factors
Factor 1: 0.04282 + 0.11896 B**(1)
Denominator Factors
Factor 1: 1 + 0.64999 B**(1)

Input Variable 2 wind

Input Variable wind
Numerator Factors
Factor 1: -0.0104 + 0.0104 B**(7)

As stated in Appendix (A), the Rational Distributed Lag (ARIMAX) model was estimated according to the conditional least squares estimation of the SEP time series, which proves its validity as a model for this market. Its residuals analysis also clearly shows its suitability; for instance, the cross-correlation function of the residuals when the SEL is considered as the input demonstrates that there is no correlation among of residuals, as shown in Table 3.71-B. In the area checking the behavior of white noise, no correlations are found among the residuals, as per Appendix (A) or Table A.1. Appendix (A) and Table 3.71-B demonstrate the autocorrelation (ACF) of the (squared) residuals related to the ARIMA section of the model, indicating that there are no serial correlations among of the (squared) residuals in the ARIMAX model. In addition, the model parameters are significant in each section (the AR and MA sections) because the t-values of the coefficients are greater than two. What is more, there is a significant coefficient related to wind power generation in Appendix (A). This result again proves that this factor influences the behavior of the SEP and the ARIMAX is a valid model, the most suitable model for investigating the impact of the load and wind on prices in the Spanish electricity market.

In contrast with the SEP, according to Table 3.72-A and 3.72-B, the ARIMAX model indicates in Appendix (B) cannot be applied to the Iranian electricity price. The residual analysis of this model clearly proves that there is no type of relationship between the IEP and IEL time series; see Table B.1 in Appendix (B).

Table 3.71: The residuals analysis of the SEP ARIMAX model.

A- Autocorrelation Check of Residuals related the ARIMA section of our model.

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.77	1	0.0959	-0.004	-0.009	-0.011	-0.010	-0.045	0.000
12	6.84	7	0.4456	0.007	0.003	-0.027	-0.020	0.022	-0.042
18	11.98	13	0.5295	-0.038	-0.026	0.017	-0.029	0.031	-0.011
24	12.91	19	0.8433	0.005	-0.020	0.014	0.002	-0.006	0.010
30	19.21	25	0.7868	0.048	-0.004	0.027	0.009	0.040	0.023
36	33.34	31	0.3539	0.028	0.054	0.041	-0.041	0.047	0.049
42	38.92	37	0.3833	0.029	-0.021	0.026	0.015	-0.037	0.032
48	49.26	43	0.2371	-0.021	-0.015	-0.050	0.062	0.007	-0.037

B- Cross-correlation Check of Residuals with Input load (ARIMAX model).

To Lag	Chi-Square	DF	Pr > ChiSq	Crosscorrelations					
5	4.49	3	0.2130	0.003	0.018	0.038	0.022	-0.039	-0.003
11	13.15	9	0.1561	0.063	0.036	0.017	0.003	-0.042	-0.002
17	15.29	15	0.4309	0.004	-0.010	-0.030	-0.013	-0.023	-0.008
23	16.91	21	0.7164	0.030	0.009	0.014	-0.013	0.003	0.005
29	44.26	27	0.0194	0.082	-0.010	0.050	-0.102	-0.014	-0.057
35	52.37	33	0.0174	0.011	-0.022	0.014	-0.030	0.051	-0.051
41	57.92	39	0.0260	-0.045	0.023	0.013	-0.009	0.028	0.034
47	64.99	45	0.0271	0.028	-0.061	0.033	-0.017	-0.010	0.002

Table 3.72: The residuals analysis of the IEP ARIMAX model.

A- Autocorrelation Check of Residuals related the ARIMA section of model.

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	9.22	1	0.0024	0.003	0.002	-0.011	-0.004	-0.003	-0.091
12	26.48	7	0.0004	0.003	-0.057	0.001	0.104	-0.039	-0.006
18	31.61	13	0.0027	-0.023	0.047	-0.002	-0.000	-0.033	-0.028
24	60.11	19	<.0001	-0.014	-0.068	0.032	-0.069	0.105	0.063
30	69.67	25	<.0001	-0.055	-0.013	-0.027	0.013	-0.067	-0.005
36	93.65	31	<.0001	0.096	-0.060	0.020	0.071	-0.003	-0.056
42	101.55	37	<.0001	0.020	-0.029	-0.036	-0.017	0.018	0.062
48	117.81	43	<.0001	-0.031	-0.020	-0.021	0.023	0.065	-0.088

B- Cross-correlation Check of Residuals with Input load (ARIMAX model).

To Lag	Chi-Square	DF	Pr > ChiSq	Crosscorrelations					
5	7.41	4	0.1157	0.062	-0.017	0.023	0.024	-0.038	-0.011
11	14.08	10	0.1695	-0.015	0.050	0.043	-0.008	-0.034	0.019
17	23.04	16	0.1127	0.005	0.017	0.001	-0.009	-0.048	0.074
23	28.88	22	0.1482	-0.001	0.008	-0.043	0.054	-0.006	0.023
29	38.14	28	0.0958	0.025	0.006	-0.040	0.060	-0.039	-0.035
35	40.33	34	0.2105	0.003	-0.003	-0.011	0.016	0.030	-0.027
41	43.24	40	0.3345	-0.034	-0.002	0.019	0.005	0.027	-0.019
47	53.60	46	0.2058	0.038	-0.015	-0.070	0.007	0.044	-0.031

As explained previously, load (as demand) is introduced into a competitive and developed electricity market as the significant index/ factor that normally has a sizeable impact on market price (Kotler and Armestrong, 2010; Nicholson and Snyder, 2011; Weron, 2007).

Therefore, the above results point to further research into whether other economic factors or indices might have an impact on the Iranian electricity market. In order to attain this strategic information, the behavior of Iranian electricity prices and its relationship with four other important economic factors in the Iranian energy market will be examined.

Chapter 4

4 Investigation of the impact of four economic factors on the behavior of Iranian electricity prices and forecasting

As previously mentioned, "Since the late 1980s, policy makers and regulators in a number of countries have liberalized, restructured or "deregulated" their electric power sector, typically by introducing competition at the generation and retail level. These experiments have resulted in vastly different outcomes—some highly encouraging, others utterly disastrous. However, many countries continue along the same path for a variety of reasons" (Sioshansi 2008). Due to the many advantages of having a developed electricity market, Iranian governmental organizations have been trying to change the fundamentals of the electricity market, such as the distribution sector, from monopolization to privatization (Khalili and Mehri 2007). Examining the market and its components and structures is of great importance in order to maintain and improve market position. For instance, Chris Harris (2011) shows how the energy market works according to technical and quantitative approaches by investigating electricity market policies. Changes in the market and its prices usually replicate from variations in economic indices and factors.

As explained in Chapter Two, the size of the demand, the availability of different means of power generation, fuel costs, and plant availability have a great deal of impact on price and its behavior in the growth rate of electricity markets (USA energy administration 2014; Le & Vinh 2011). On the other hand, a country's rate of inflation and its exchange rate, as two important macroeconomics (Aggarwal et al. 2009; Le & Vinh 2011; Yu et al. 2013; Sameti et al. 2004; Kilian 2008; Adaramola 2011), plus energy prices in general also play significant roles in both economic activities and the energy market (Asafu-Adjaye 2000; Kilian 2008; Le and Vinh 2011).Taylor (2001), mentioned "the role of the exchange rate in monetary policy rules", while Adao (et al. 2009) and others have pointed to the relevance of the exchange rate regime in monetary policy stabilization. Yu and Mallory drew attention to the "exchange rate effect on carbon credit price via energy markets" (Yu et al. 2013). Meanwhile, Asafu-Adjaye (2000) investigated the relationship between energy prices and economic growth using the time series approach for Asian developing countries such as India, Indonesia, the Philippines and Thailand, and closer to home, Moutinho and Carrizo (2011) determined what role natural gas prices played in Spanish electricity prices.

The role of the "stock exchange in corporate governance" was addressed by Christiansen and Koldertsova in 2008, while Simanovsky (2009) pointed out that "understanding how the stock exchange works is absolutely necessary when entering investing. Today, a large portion of the population is directly or indirectly involved in the capital market". Mohsen Bahmani and Oskookee, using annual data from 1959-1990, determined that the severe rate of inflation after the revolution (1978-79) was due to the creation of the black market and the performance of the exchange rate there (Bahmani-Oskooee 1995). Jensen and Tarr (2003) explained in their studies that Iran, because of its commitment to the World Trade Organization, had to give up nontariff barriers, the dual exchange rate system, and highly subsidized prices on petroleum products, and also use market mechanisms as a means of regulating foreign trade.

Energy price is another feature of a country's economy. Boqiang & Dunguo (2008) assessed the role of the price of oil and coal in the Chinese economy with relation to net imported oil. Kilian (2008) described the economic effects of energy price shocks in the U.S in his studies, Finn, (2000) wrote about perfect competition and the effects of increased energy prices on economic activity. In another example, Emery and Liu (2002) presented an analysis of the relationship between the price of electricity and natural gas futures and demonstrated their cointegration. Fischer and Merton (1984) explained the importance of the behavior of the stock market on macroeconomics, introducing it as "a good predictor of the business cycle and components of the GNP". As "The term stock market can be used to denote an individual stock exchange in various places or one market comprising all individual stock exchanges in a country" (Bhole 2004), Cong et al. (2008), using multivariate vector auto-regression, investigated the interactive relationships between the stock exchange price (as one indicator of the stock market), oil price shocks and the Chinese stock market. Most of these kinds of studies have led the researcher to examine the role of economic indicators and factors in the energy market.

Chapter Three of this thesis proved there was no linear or nonlinear relationship between electricity load (as demand) and electricity prices in the Iranian electricity market. This raises the question of what economic factors actually have an impact on this energy market and its electricity price. To answer this, the importance of the behavior of other economic indicators in the Iranian electricity market must be evaluated in order to obtain more strategic information and scientific knowledge about this market.

The research performed in Chapter Two of this paper ascertained that there were fewer considerations and limited study related to evaluating the importance of other economic factors and indicators—such as foreign exchange rates, the stock exchange and natural gas and oil prices—in the Iranian electricity market. As these have a significant influence on energy trading and commerce, their impact on prices has been assessed using the time series analysis approach.

Several of the aforementioned studies point towards the investigation of the role of the USD/IRR exchange rate (IDEX) on prices in the Iranian electricity market. This may help provide an understanding of how the fluctuation of the exchange rate influences the behavior of Iranian electricity prices (IEP). In addition, the Tehran stock market is considered the largest and most important stock market in the Islamic Republic of Iran; therefore, the Tehran stock exchange price index (TEPIX) has been chosen to explore its relationship with the IEP. Another point in the thesis examines the existence of a relationship between the Henry Hub Natural Gas Spot Price (HHSP), the world's most important natural gas spot market (EIA 2014) and the IEP time series. On the other hand, as it is mentioned in Chapter two, the world oil price has significant impacts on the energy markets. Similarly, this research surveys the relationship between the Europe Brent Spot Oil Price FOB (EBSP) and Iranian electricity price.

In this chapter, first there will be a data description of the factors—the time series involved. Then, the association or relationship between these four time series will be examined in twos: the IDEX, TEPIX, HHSP and EBSP time series.

After that, there will be an attempt to discover whether or not there is any relationship amongst these factors. These evaluations will then be used to investigate whether or not there is a relationship between these factors and the IEP. The end result will help decision makers to know how the Iranian electricity market behaves.

4.1 Data description and Methods

The importance of the Henry Hub Natural Gas Spot Price (HHSP) Europe Brent Oil Spot Price (EBSP), the Tehran Stock Exchange Rate (TEPIX) and the USD/IRR exchange rate (IDEX) on the Iranian economic market have led the researcher to evaluate their impact on prices in the Iranian electricity market. A three-year period of research was given over to each economic factor in a time series, the same amount of time as the Iranian electricity price (IEP) time series; see Figure 4.1.

Similar to the IEP, a total of 1095 samples have been taken for the four indices listed in the previous paragraph. For the IDEX and TEPIX, no rates are quoted on Iranian holidays (Central Bank of the Islamic Republic of Iran 2014; Tehran Stock Exchange, 2013), which means the previous day's rates will be applied in these time series. These observations cover all weekdays and start from March 21, 2007 and end March 20, 2010. The IDEX data has been provided by Iranian Central Bank (Central Bank of the Islamic Republic of Iran, 2014). The Tehran stock exchange, being the leading stock market in Iran, has been evaluated as to the impact of the TEPIX on Iranian electricity prices. The required information has been provided by the daily TEPIX report issued by the market's website (Tehran Stock Exchange, 2013).

Another evaluation covers the role of the Henry Hub natural gas spot price (HHSP) in the Iranian electricity market. The information for the HHSP time series is attained from the US Energy Information Administration (World Bank Publications, 1999; Energy Equity Group, 2014; EIA, 2014). The Brent Spot Oil Price FOB (Dollars per Barrel) is another international benchmark in the energy market (Energy and Capital, 2014; USA Energy Administration, 2014). Therefore, the relationship between these two spot prices will be examined in order to choose one of them to investigate its role in the Iranian electricity market.

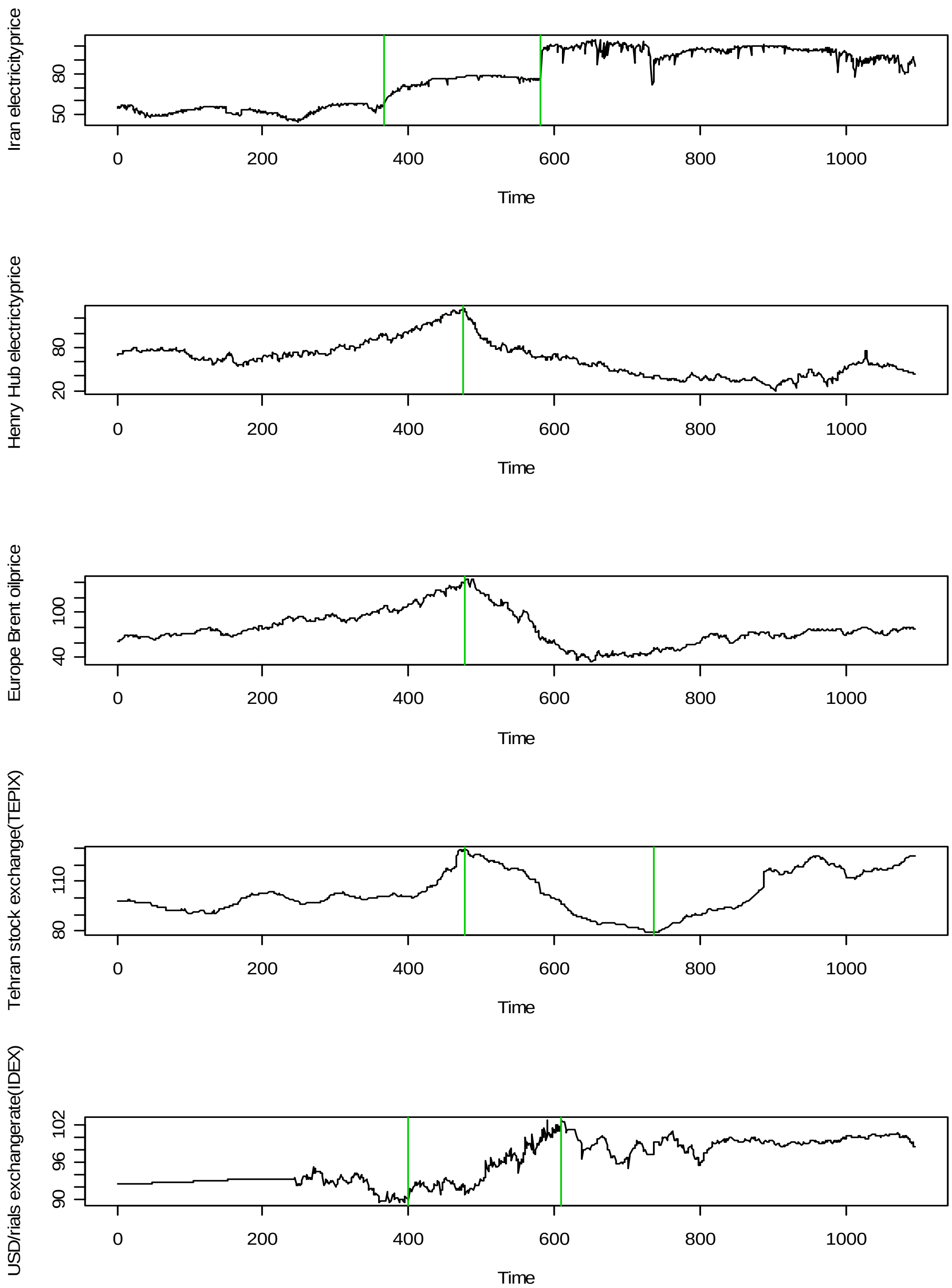
Similar to the IEP time series, these factors behave differently in each section of their respective time series, as seen in Figure 4.1. Therefore, in order to attain more detailed information about them, they are considered according to different methodologies of analyzing statistical time series; see Figure 4.2 and Table 4.1.

The box plot was first introduced as one of the discovery statistics methods by Tukey in 1977 (Dawson, 2011). This plot can display the range, the interquartile range, the median, the lowest (minimum) score, and the highest (maximum) score, etc. (see Williamson et al., 1989; Hintze and Nelson, 1998). Figure 4.2 expresses the different behavior patterns of each time series. For example, the box plot of the daily HHSP time series indicates that the first quartiles in the first section are higher than the second. Also, the second section is not as large as the first. However, in the TEPIX time series, the first quartiles of second and third section can be seen as the same, although the box plot of the second section is different. On the other hand, the median line, which indicates the median observation of the time series, is found in different positions in each part of these four time series. What is more, there are some points outside the roots in the first and third quartiles; these are known as outliers: see Figure 4.2. These box plots prove that each of the time series behaves differently over time.

These results are also represented by means of descriptive statistics for these four time series, as shown in Figure 4.3. The HHSP and EBSP exhibit asymmetry in both parts of their time series, as their skewness values are either positive or negative in Table 4.1. The p-values of the skewness test are greater than 0.05 and a null hypothesis of skewness=0 is accepted for the first and second sections of each time series; while the kurtosis test results in a p-value greater than 0.05 (predetermined significance level). In other words, there are no tails on the right or left side of each distribution. The results of the "Jarque-Bera Normality Test" show that the p-values in these time series are less than 0.05. Therefore, they prove that the skewness and kurtosis do not match a Gaussian distribution in any of these time series; see Table 4.1 and Figure 4.3, although the TEPIX and IDEX behaved differently in each section of their time series; see Table 4.1 and Figure 4.1. In some sections of these time series, the skewness p-value is less than 0.05 and greater than 0.05 in other sections. Overall, the "Jarque-Bera Normality Test", when the p-value is less than 0.05, also indicates a tail in the distributions, which are not asymmetrical.

On the other hand, the histograms clearly display that no unit identification distribution exists in any series. In addition, the ACF and PACF from squared of data in these time series, even after taking out the first-order differences, also indicate no stationary behavior exists, as observed in Figure 4.4. The scale of the time series is changed into the same scale; for a more detailed explanation about these factors, see the other sections in this chapter.

A time series analysis approach will be presented so as to evaluate the impact of these factors on the IEP (based on Rials/kWh). This means, there will be an investigation as to the existence of any linear or nonlinear relationship between each of these indices or factors and the market price. Prior to these evaluations, the existence of a relationship between of each of these four factors will be surveyed to examine some assumptions in the next section.



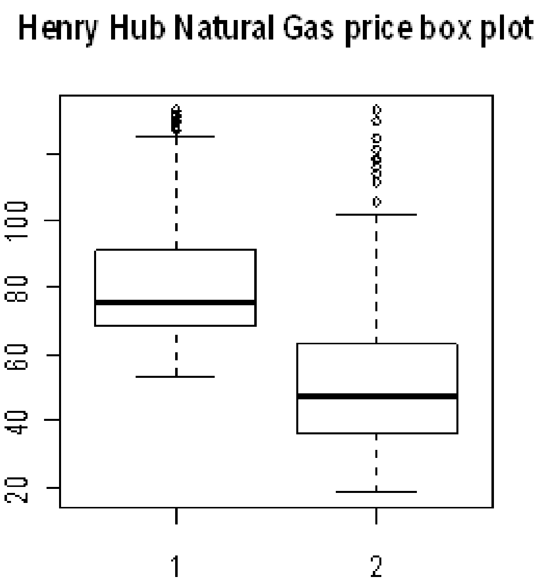
Note: First time series-daily Iranian electricity price (IEP). **Second time series**- Henry Hub natural gas spot price (HHSP). **Third time series**-European Brent oil spot price (EBSP). **Fourth time series**- daily USD/IRR exchange rate (IDEX). **Fifth time series** - Iranian (Tehran) daily stock exchange price (TEPIX).

Figure 4.1: the IEP time series and the four economic factors.

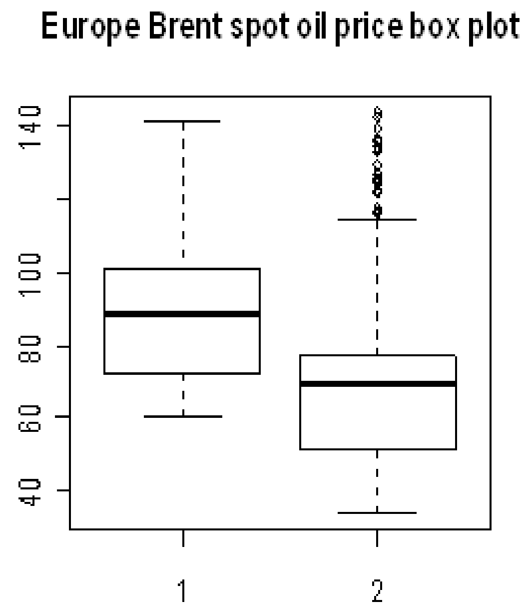
Table 4.1: Summary descriptive statistics for four economic factors time series;
Note : **First factor** -daily Henry Hub spot gas price time series- **Second factor**- daily Europe Brent spot price oil time series. **Third factor**- daily (USD/Rials) foreign Exchange rate. **Fourth factor**- Iranian (Tehran) daily stock exchange

Time series	No.Ob	Time span	Median	Min	Max	Mean	Stdev	Skewness*	Kurtosis*	Jarque – Bera test *
	Henry Hub spot gas price									
H. H. gas price time series First section	475 (1-475)	21/03/2007-8/07/2008	75.30	53.00	133.10	81.342	19.29	1.083 (1)	0.297 (0.906)	95.3849 p Value: < 2.2e-16
H. H. gas price time series Second section	(620) (476-1095)	9/7/2008-20/03/2010	47.20	18.30	133.1	51.63	19.916	1.299 (1)	1.9206 (1)	272.2632 p Value: < 2.2e-16
	Europe Brent spot oil price									
E. B.spot oil price time series First section	478 (1-478)	21/03/2007-11/7/2008	88.71	60.11	141.24	89.661	20.039	0.763 (1)	-0.2908 (0.069)	48.329 (p Value: 3.203e-11)
E. B.spot oil price time series First section	617 (479-1095)	12/07/2008-20/03/2010	69.45	33.73	143.95	69.45	22.682	1.078 (1)	1.258 (1)	161.8497 (p Value: < 2.2e-16)
	Tehran stock exchange price (TEPIX)									
T.stock exchange price First section	478 (1-478)	21/03/2007-11/07/2008-	100.02	90.66	129.17	100.33	7.23	1.870 (1)	4.717 (1)	729.9279 (p Value: < 2.2e-16)
T.stock exchange Second section	257 (479-610)	12/07/2008--20/11/2008	98.514	79.65	129.17	100.72	16.54	0.265 (0.958)	-1.5393 (2.360327e-07)	28.0594 (p Value: 8.072e-07)
T.stock exchange Third section	360 (611-1095)	21/11/2008-20/03/2010	98.31	79.55	125.81	107.19	14.36	-0.454 (0.00021)	-1.3296 (1.304057e-07)	38.6657 (pValue: 4.016e-09)
	USD/R Exchanges rate(IDEX)									
Exchange rate First section	400 (1-400)	21/03/2007-24/04/2008	92.81	89.47	95.03	92.58	1.066	-1.492 (1.760998e-34)	1.973 (1)	216.2831 (pValue: < 2.2e-16)
Exchange rate Second section	210 (401-735)	25/04/2008-24/03/2009	93.805	90.65	102.68	95.027	3.366	0.556 (0.9995)	-1.0069 (0.00144)	19.5512 (p Value: 5.682e-05)
Exchange rate Third section	485 (736-1095)	23/11/2008-20/03/2010	99.24	94.88	102.49	98.99	1.226	-0.79804 (3.615138e-13)	1.0234 (0.999)	73.6629 p Value: < 2.2e-16

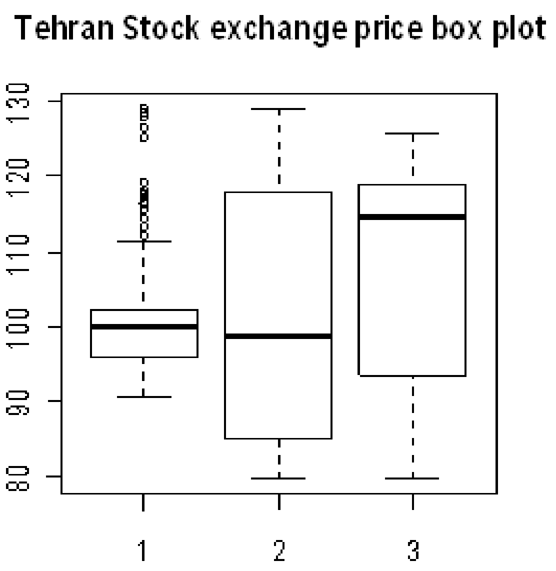
A- Box plot of daily HHSP time series.



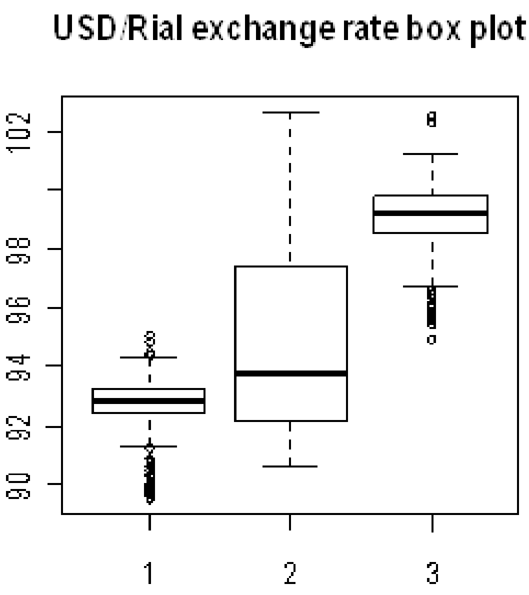
B- Box plot of daily EBSP time series.



C- Box plot of daily TEPIX time series.

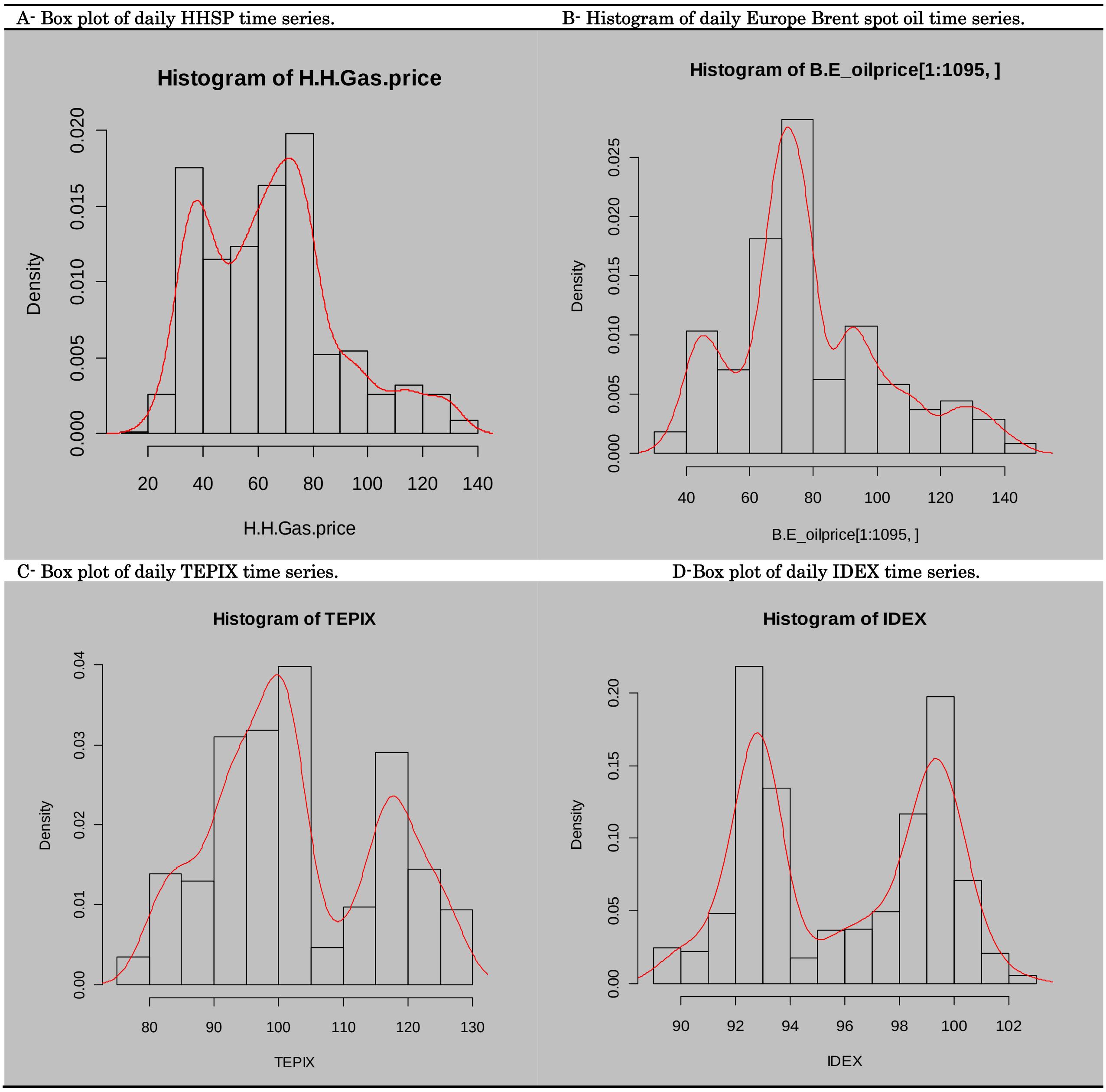


D- Box plot of daily IDEX time series.



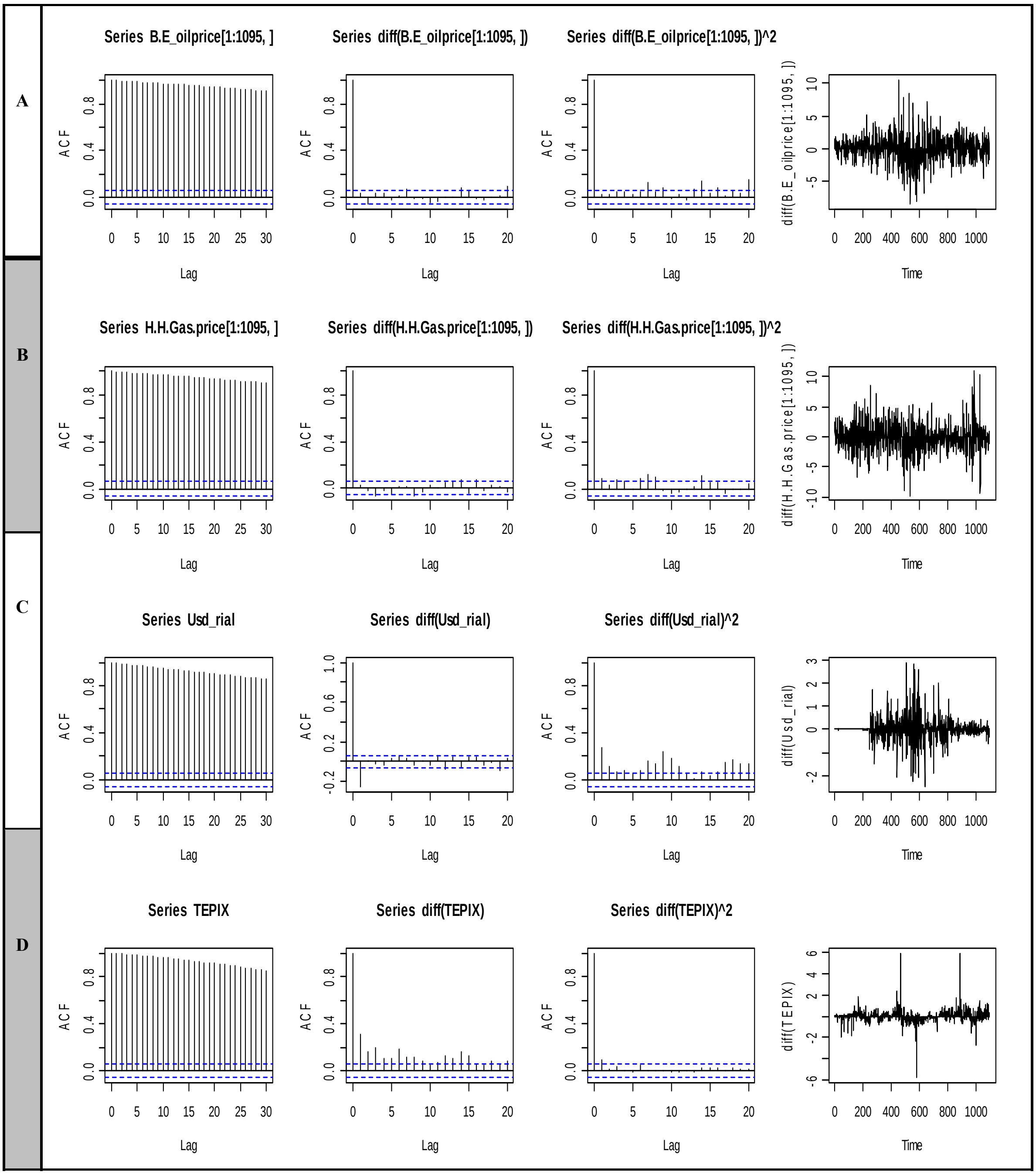
Note: Four time series are included: **A**-Daily HHSP time series. **B**-Daily EBSP time series. **C**- Daily TEPIX time series. **D**-Daily IDEX time series.

Figure 4.2: Box plot of the four time series.



Note: Four time series are included: **A**-Daily HHSP time series. **B**-Daily EBSP time series. **C**- Daily TEPIX time series. **D**-Daily IDEX time series.

Figure 4.3: Histogram of the four time series.



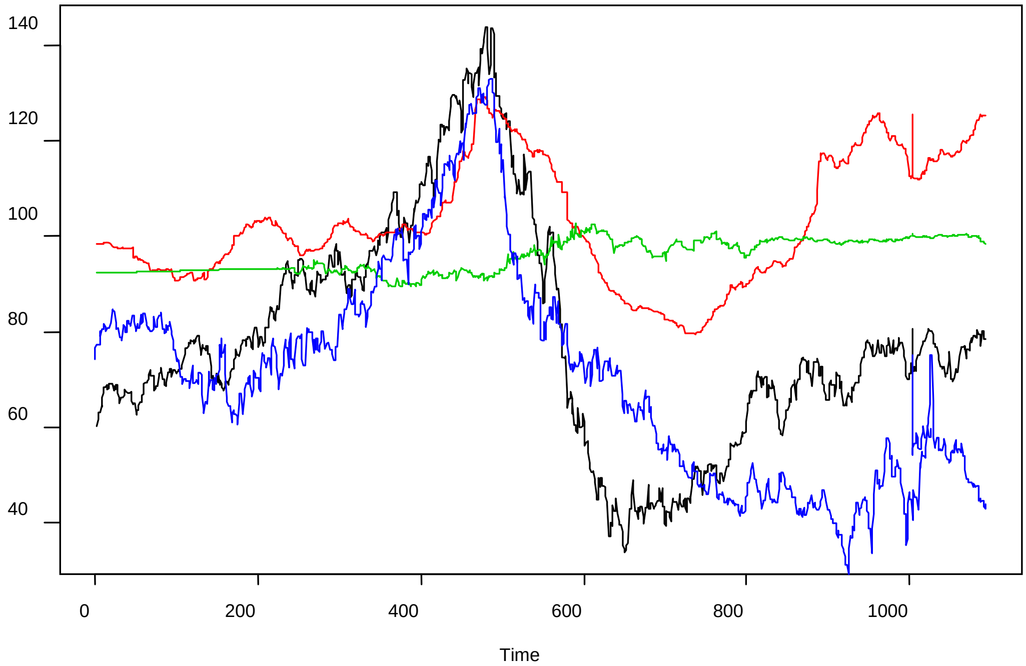
Note: Four time series are included: **A**-Daily HHSP time series. **B**-Daily EBSP time series, **C**- Daily TEPIX time series. **D**-Daily IDEX rate time series.

Figure 4.4: ACF and PACF (squared) of the four time series (after taking out first-order difference).

4.1.1 Investigating the relationship between the four economic factors

4.1.1.A Pearson's Correlation Coefficient Method

In the section, there will be an attempt to determine whether there is a relationship between the economic factors (the daily HHSP, EBSP, TEPIX and IDEX time series). It will also be examined whether a linear regression model can be applied to these economic factors or the four time series. In Figure 4.5, the different and non-stationary behaviors of each time series have given the researcher cause to believe that the investigation if such a relationship exists may be complicated; also see Section 4.1.



Note: **Red**- daily TEPIX time series. **Green**- daily IDEX time series. **Blue**- daily HHSP time series. **Black**- daily EBSP price time series.

Figure 4.5: overlapping the four time series;

One assumption is to follow the existence of the multicollinearity amongst of these economic factors. Multicollinearity occurs when there is a linear relationship among of one or more independent variables (Matt & Golder, 2014; Allison, 1999). This entails defining the above four factors or time series as independent or explanatory variables, and the Iranian electricity price time series as an independent or response variable. The existence of multicollinearity is not “a violation of the assumptions underlying the use of regression analysis” (Chalmer, 1986). “Perfect multicollinearity is obtained whenever one independent variable is the perfect linear function of one or more of other independent variables in a regression equation” (Allen, 2004).

On the other hand, “there are numerous statistical procedures that we can also employ to examine bivariate relationships” (Allen, 2004). These methods include Karl Pearson’s correlation coefficient (Pillwein, 1970), Kendall and Spearman’s rank correlation coefficient (R Documentation, CRAN, 2014; Pillwein, 1970), or the ANOVA Chi-Square Test (Allen, 2004), which includes the association between two variables. Consequently, these provide procedures to test statistical significance and measure data association. The tests help examine hypotheses as to the relationship between variables in the population. Also, the measure of association reflects on the strength of such relationships as to strong, weak or no relationship between time series (Pillwein 1970; O’Rourke et al. 2005).

The significant advantage of the correlation coefficient test is that it does not depend on the units of the variables. Therefore, it can be used to compare any two variables regardless of their units (SurgicalCriticalCare website, 2013). These correlation calculation methods are based on the nature of the variables (and their relationships), the various levels of measurement, and their differences; see O’Rourke et al., (2005) and Table 4.2. For instance, the Chi-Square Test is applied when the variables are nominal.

The Pearson correlation producer is applicable when the nature of the variables—or their relationships—is an interval or a ratio level of measurements (O’Rourke et al. 2005). Kendall and Spearman’s rank correlation coefficient producer is applied when the natures of the variables are ordinal levels. These methods estimate a rank-based measure of association and are employed when the number of the sample population is not large enough to use the Pearson test (Momeni, 2011); these tests may be used if the data does not necessarily come from a bivariate normal distribution (R Documentation, CRAN, 2014; Yau, 2013)

Table 4.2: The statistics for pairs of variable values (O’Rourke et al. 2005).

Nature of variables	Nominal level	Ordinal level	Interval level	Ratio level
Ratio level	Anova	Spearman correlation	Pearson correlation or Spearman correlation	Pearson correlation or Spearman correlation
Interval level	Anova	Spearman correlation	Pearson correlation or Spearman correlation	
Ordinal Level	Kruskal-Wallis test	Spearman correlation	----	----
Nominal Level	Chi-Square test	----	----	----

One of the most often used statistical quantities is Pearson’s correlation coefficient, (symbolized here as “r”). This test measures the degree of linear interrelation between two pieces of sampled data (two variables) with a size of n, where the variables are measured over time. The general aim in correlation analysis, such as the bivariate time series, is to evaluate the possibility that one time series affects another as an independent variable (see Yau, 2013).

Here, the research will attempt to evaluate the influence of each factor or index on the others. The first step is to examine the null hypothesis, that the correlation between two interval-or-ratio-level variables is zero in the population according to Pearson's product-moment correlation test (O'Rourke et al., 2005; Field, 2009). In other words, the null hypothesis where the "true correlation is equal to zero" will be tested (R Documentation, CRAN, 2014).

The result indicates whether there is a correlation between a pair of time series (daily HHSP time series, daily EBSP time series, daily TEPIX time series, and daily IDEX time series). These methods also clarify the strength of influence of each time series. A Pearson can range from -1.00 through +1.00, with large absolute values indicating a strong relationship. A value equal to 0 means there is no relationship between the variables (O'Rourke et al., 2005). Karl Pearson's correlation coefficient variable quantitatively measures the vastness to which two variables are correlated. In general, for two set variables x and y with a size sample equal to n, the Pearson correlation coefficient, r, is given mathematically by Pillwein (1970) in Eq. (4.1):

$$r = \frac{\text{covariance}(x, y)}{\sqrt{\text{var } x}\sqrt{\text{var } y}} = \frac{\text{cov}(x, y)}{\sigma_x \sigma_y}$$

Eq. 4.1

Overall , $\bar{x}$ and $\bar{y}$ are the actual means of data. $\sigma_X$and σ_Y are standard deviations of the sample data for each variable of x and y; (see Sharma, 2008).

Where

$$\text{cov}(x, y) = \frac{1}{n}\sum(x - \bar{x})(y - \bar{y})$$

Eq. 4.2

Pearson's correlation coefficient has some disadvantages, as it only evaluates the linear relationship between variables, and it computes the value r as correlation coefficient value. However, this correlation coefficient producer has some advantages, too: it is useful for exhibiting the relationship between two interval-ratio variables; it is employed to calculate the strength of correlation as a numerical number between -1 and 1, and it shows the (negative or positive) direction of the association between two variables (Sharma, 2008).

Therefore, it can be used to measure the relationship between each pair of time series (see following sections). Normally, the correlation coefficient is attained by three kinds of R code commands: cor(), cor.test() and rcorr() (Quik-R,2015; Yau 2013). The features of these functions are shown in Table 4.3 (see Field, 2009). Here, in order to calculate the p-value and test hypotheses on the relationship between variables in the population (O'Rourke et al., 2005; Sharma, 2007), it is necessary to use the cor.test() function. In contrast with this function, the cor() function is used in order to evaluate the (positive or negative) direction of correlations and distinguish the degree of strength in the association between variables, whose square value is shown by r. Both of these functions are sections of the base system in R (R Documentation(CRAN), 2014; Field, 2009; Yau, 2013)

Table 4.3: Attributes of different functions for obtaining correlations (Field, 2009).

Function	Perason	Spearman	Kendall	P-value
Cor()	*	*	*	
Cor.test()	*	*	*	*
Rcorr()	*	*		*

In Table 4.4, the p-value of Pearson's product-moment correlation test and the numerical correlation coefficient of this method are represented for each pair of factors or time series. These pairs are defined as:

- [The daily IDEX and TEPIX time series].
- [The daily IDEX and HHSP time series].
- [The daily HHSP and TEPIX time series].
- [The daily HHSP and EBSP time series].
- [The daily IDEX and EBSP time series].
- [The daily TEPIX and EBSP time series].

Table 4.4: Pearson correlation coefficient between the four our economic factors;

Pearson's Correlation Coefficient Method	function	Daily IDEX and daily TEPIX time series	Daily IDEX and daily HHSP time series	Daily HHSP and daily TEPIX time series	Daily HHSP and daily EBSP time series	Daily IDEX and daily EBSP time series	Daily TEPIX and daily EBSP time series
Pearson's Correlation coefficients for each pairs of our factors (r)	cor()	0.06190	-0.7194	0.24752	0.7831959	-0.58351	0.6165314
p-value of the Pearson's product-moment correlation test	cor.test()	p-value = 0.04055	p-value < 2.2e-16	p-value < 2.2e-16	p-value < 2.2e-16	p-value < 2.2e-16	p-value < 2.2e-16
Relationship amongst factors		Weak relationship	Inverse relationship	Week relationship	Strong relation ship	Inverse relationship	Strong relationship

Table 4.4 shows that the null hypothesis of "the true correlation is equal to zero" has been rejected (R Documentation(CRAN), 2014). It is clear that the six p-values of

the Pearson's product-moment correlation test in each pair of time series are less than 0.05. In other words, there is a correlation between two of the time series (variables). For example, the p-value related to the daily USD/IRR exchange rate and the Tehran stock exchange time series is less than 0.05 in the population. Therefore, these two factors or variables are correlated in the 0.05 significant levels; the p-value is less than 0.05.

The relationship strengths of two variables are defined via Pearson's correlation coefficient (or r):

- very strong → r = 0.9 to 1.
- strong → r = 0.7 to 0.89
- moderate → r = 0.50 to 0.69
- weak → r = 0.26 to 0
- very weak or nil → r = 0 to 0.25

An absolute correlation coefficient quantity shows the strength of the correlation of two variables (Lewis-Beck et al., 2003). Here, the value of correlation coefficient (r) clearly proves there is a correlation between the pairs of factors, such in as the daily IDEX and TEPIX time series. However, the strength of this relation is still quite weak and close to zero: 0.061 (R Documentation(CRAN), 2014).

There is an odd inverse association occurring between two of the time series, the IDEX and the HHSP, evidenced by relationship strength equal to -0.719. The IDEX and EBSP time series also demonstrate a similar inverse correlation, because the resulting figure reads at -0.58351. The p-values of Pearson's coefficient correlation method are less than 0.05, which means the null hypothesis, where there is no true correlation amongst these two variables, can be rejected.

On the other hand, the null hypothesis is also rejected for two other variables, the HHSP and the TEPIX, as the p-value here is less than 0.05; but the degree of the strength relationship amongst these factors is weak, at 0.247. In the TEPIX and EBSP price, however, there is a positive correlation, shown in the Table 4.4.

4.1.1.B Scatter plots of the four economic factors

To justify these results, scatter plots were used to display their potential correlation more visually (for more information on scatter plots see Section 3.5.1 of the previous chapter 3).

In Figures 4.6 and 4.7, the relationship between each pair of factors is clearly delineated. The comparison between the results of Table 4.4 and the scatter plots exhibits some unusual and unexpected correlation behavior in these pairs of time series. For instance, in Table 4.4, the IDEX and TEPIX have a weak degree of positive correlation (r).

In contrast, their scatter plots in Figures 4.6-A and 4.7-A do not indicate any linear correlation. There may be a case of "spurious correlation" between these variables. A spurious relationship implies that "although two or more variables are correlated, these variables are not causality-related" (see Lewis-Beck et al., 2003).

There are some densely plotted points in these plots, which mean it is necessary to investigate the behavior of this pair of time series in detail and separately; see Figure 4.8. In certain periods of time, the time series, or variables, demonstrate nonlinear correlation, but in other sections, there is no correlation at all; see Figure 4.8-B.

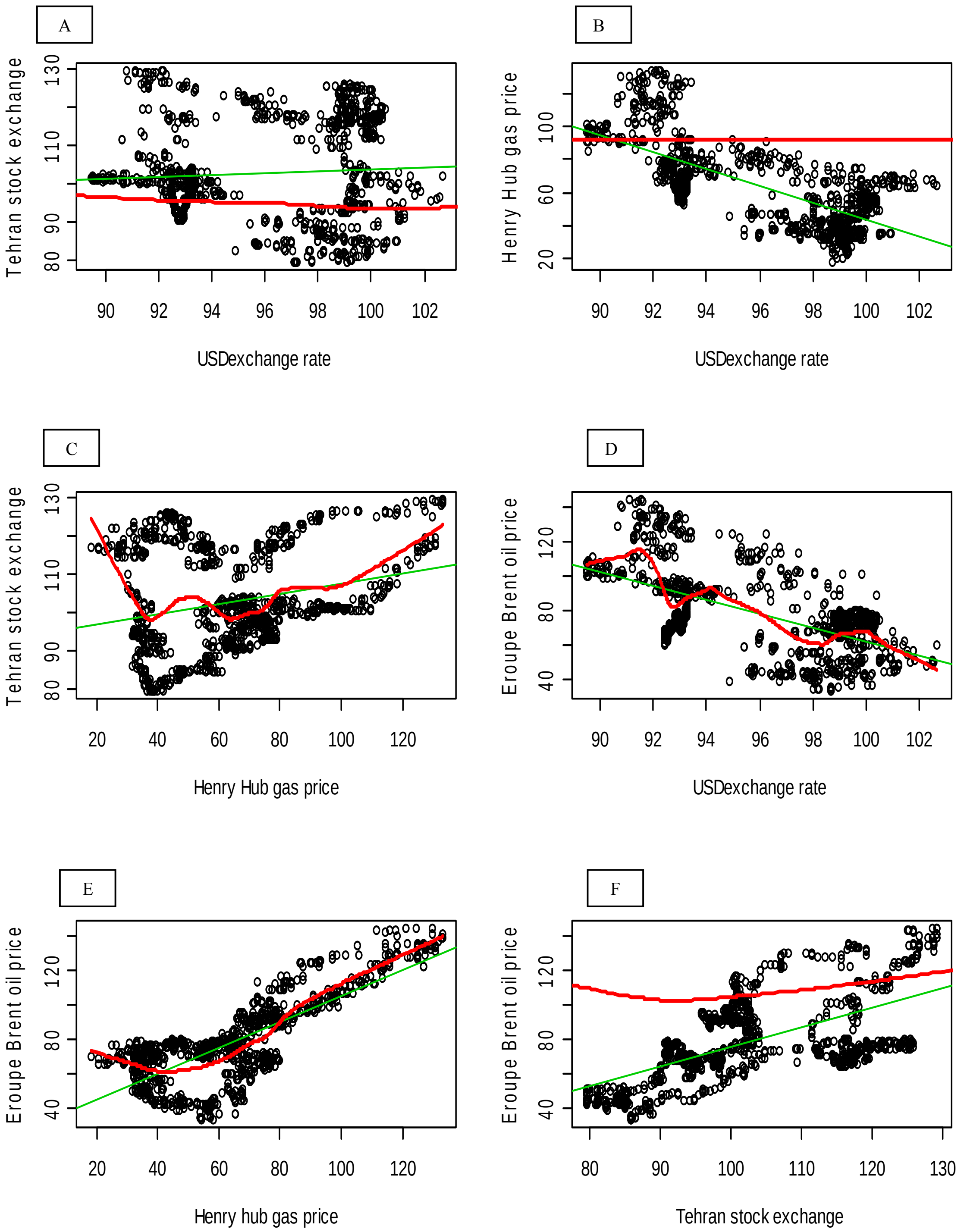
Figures 4.6-B and 4.7-B belong to the scatter plots of the IDEX and HHSP time series. Here, the red straight line has a gentle negative slope, confirming the result of Pearson's correlation method in Table 4.4.

On the other hand, Figures 4.6-C and 4.7-C point to a lack of unit linear correlation between the TEPIX and HHSP time series, in contrast with the results in Table 4.4, where the Pearson correlation test results show a high correlation. This determines there is no special unit linear relationship between these variables. The TEPIX and HHSP scatter plots have different correlations in two areas; see Figure 4.9-B. However, these economic variables do not have an unusual linear relationship. The figure has green lines to show separate value areas in the scatter plots, dividing the TEPIX time series into two areas where it has different kinds of correlations with the HHSP; both of these areas stand around 110: see Figure 4.9-D. The red lines, however, show separate periods of time in each time series; see Figure 4.9-C.

Some points in these plots can behave as outliers in this analysis. These may influence the results, so it is necessary to take them into consideration in the final evaluation (see Niven and Deutsch, 2012).

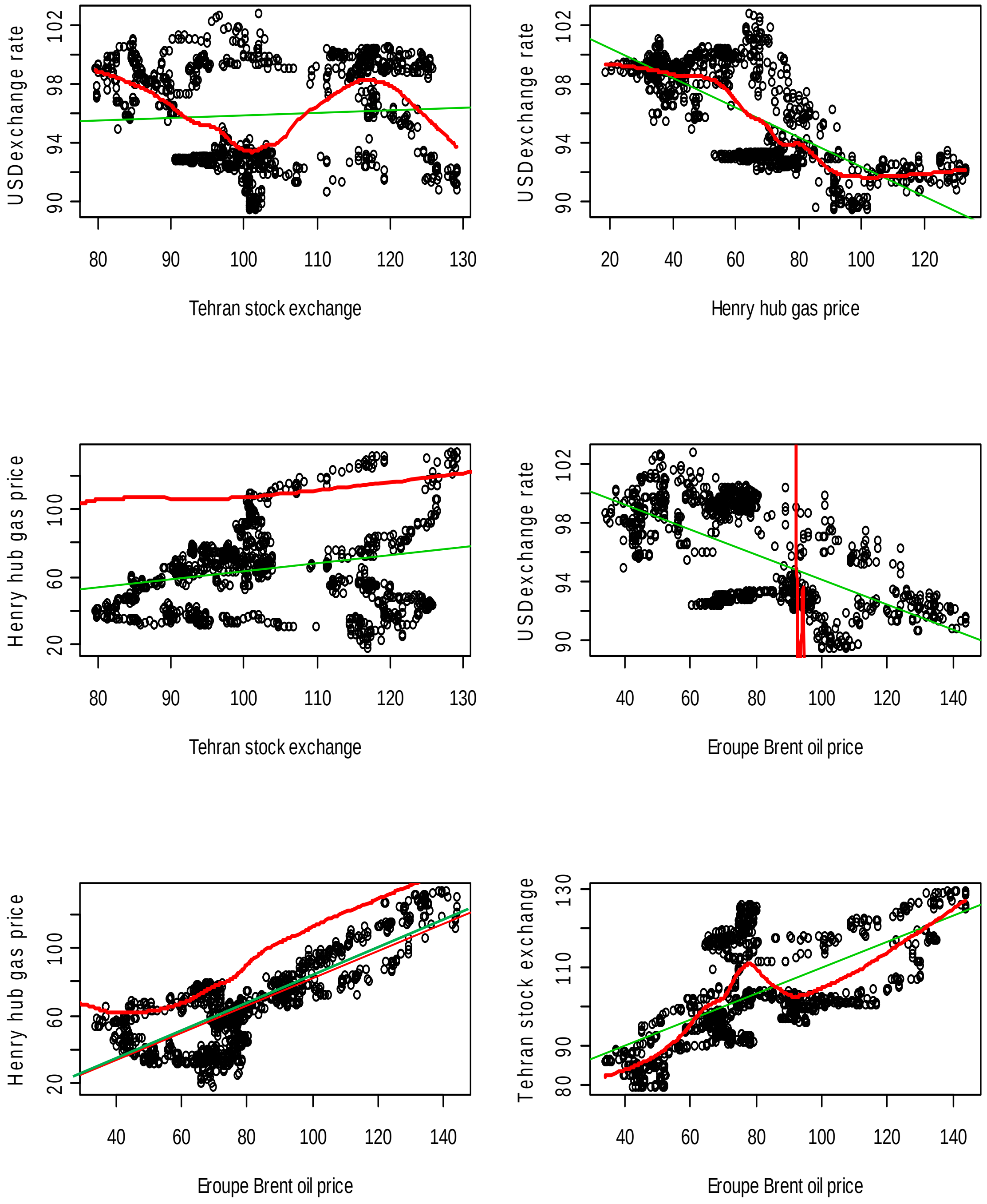
On the other hand, although the HHSP and the EBSP were proven to have an odd relationship according to Pearson's correlation coefficient value in Table 4.4, their scatter plots in Figures 4.6-E and 4.7-E display nearly compact points and an unusual correlation between two these time series. The behavior of these same densely-packed points is clearly shown in Figure 4.11-B. In certain periods of time, these two time series have a correlation with each other.

However, at other times, there seems to be no relationship between these time series at all.



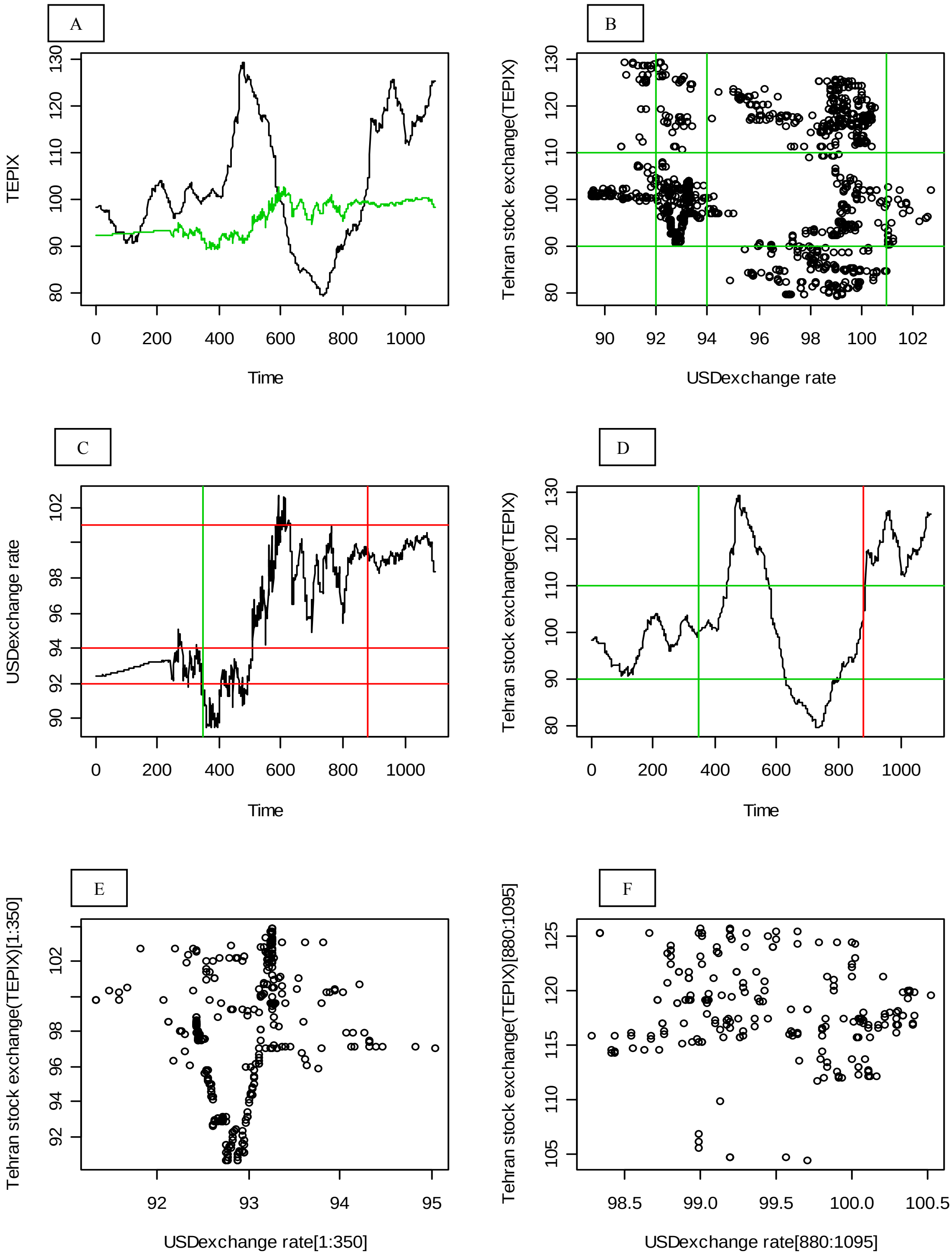
Note: factors include time series of the daily TEPIX, IDEX, HHSP and EBSP.
Here, the **green line** shows the regression line and the **red line** the correlation line.

Figure 4.6: Scatter plot of the four economic factors (two by two).



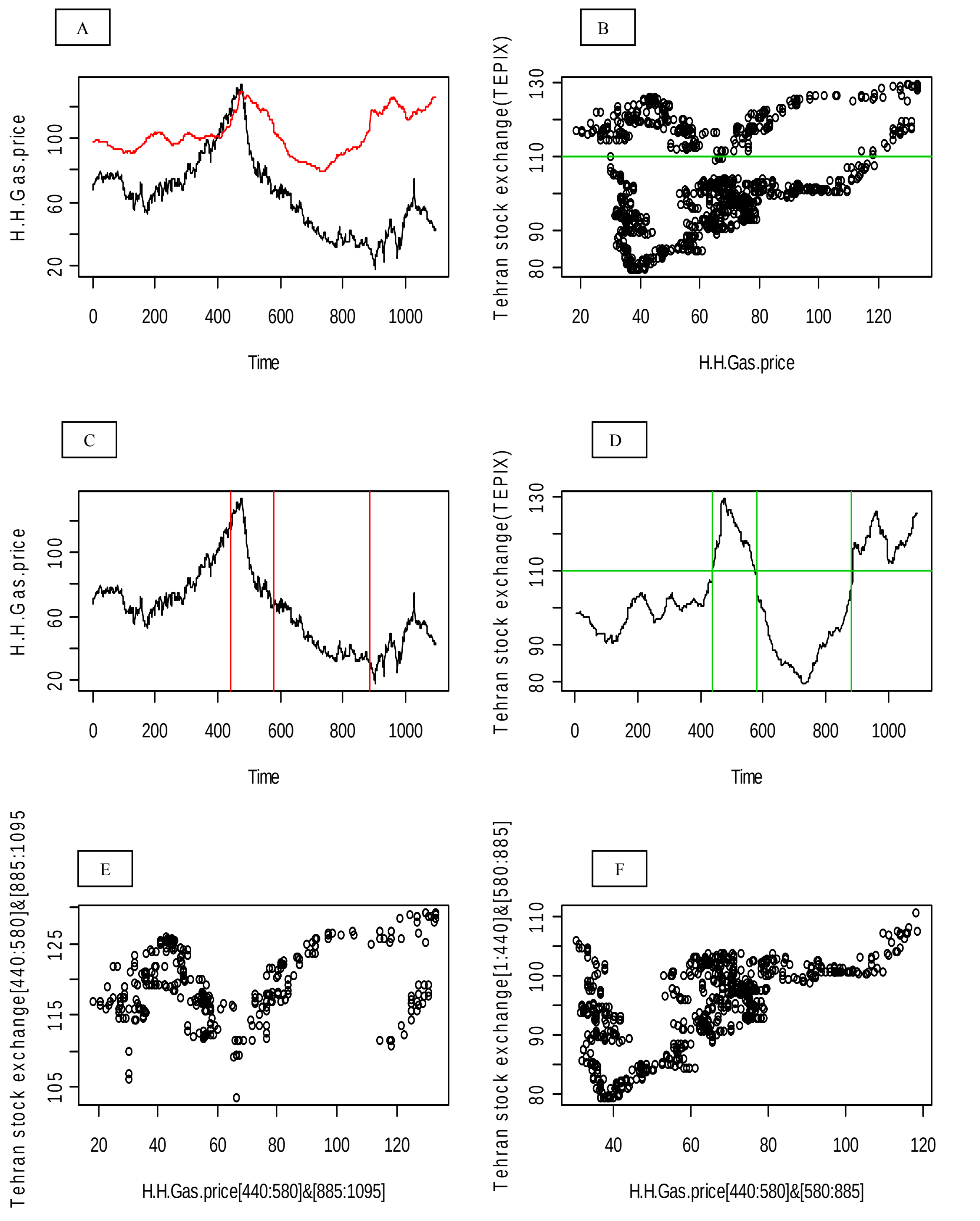
Note: factors include time series of the daily TEPIX, IDEX, HHSP and EBSP.
Here, the **green line** shows the regression line and the **red line** the correlation line.

Figure 4.7: Scatter plot of the four economic factors (two by two).



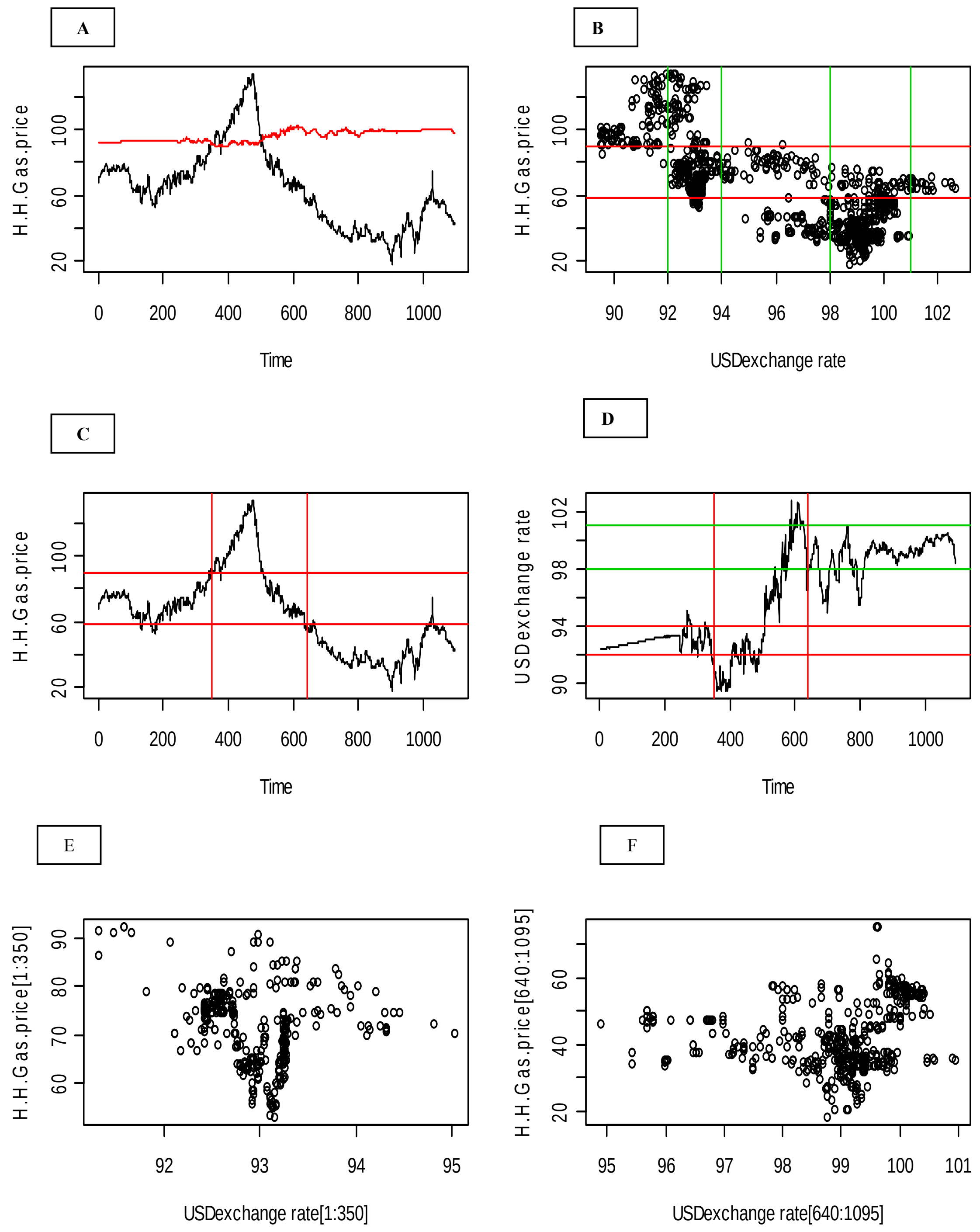
Note: In this figure, certain areas of the time series are investigated using the scatter plots to evaluate their correlation. **Green line**- plots values area separately. **Red line**- shows time periods in each series separately.

Figure 4.8: Scatter plots of the TEPIX and IDEX time series.



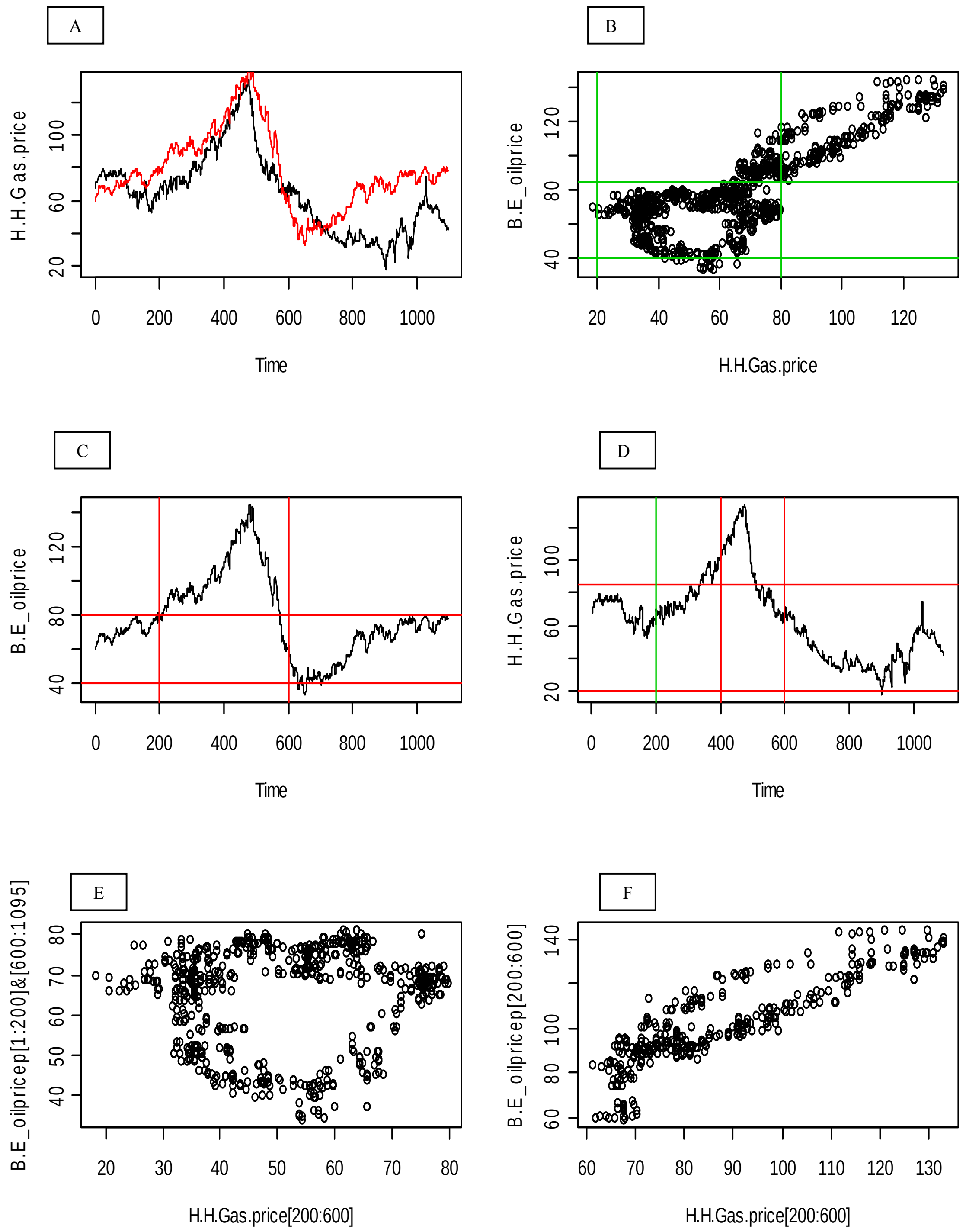
Note: In this figure, certain areas of the time series are investigated using the scatter plots to evaluate their correlation. Green line- plots values area separately. Red line- shows time periods in each series separately.

Figure 4.9: Scatter plots of TEPIX and HHSP time series.



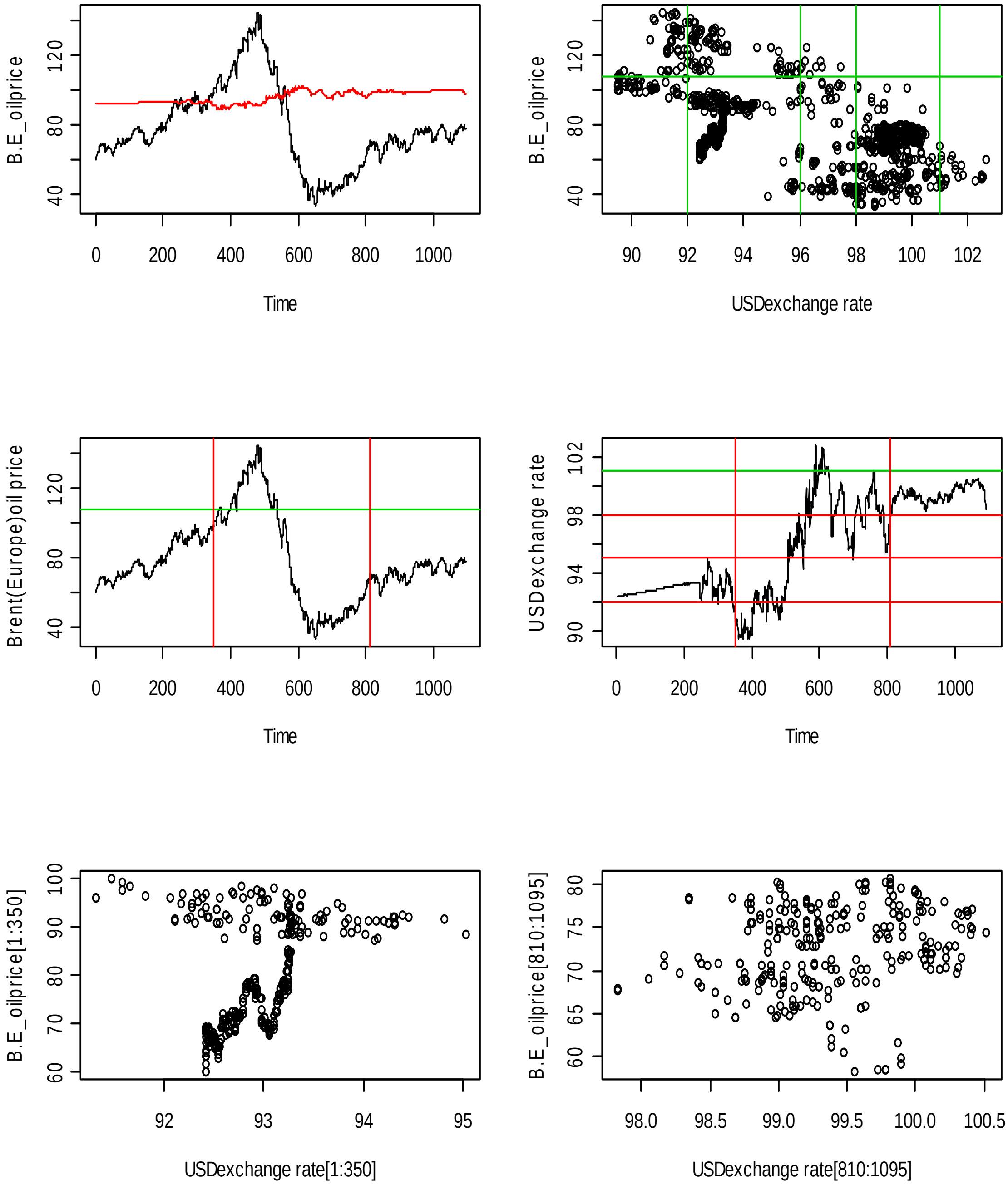
Note: In this figure, certain areas of the time series are investigated using the scatter plots to evaluate their correlation. Green line- plots values area separately. Red line- shows time periods in each series separately.

Figure 4.10: Plots of daily HHSP and IDEX time series.



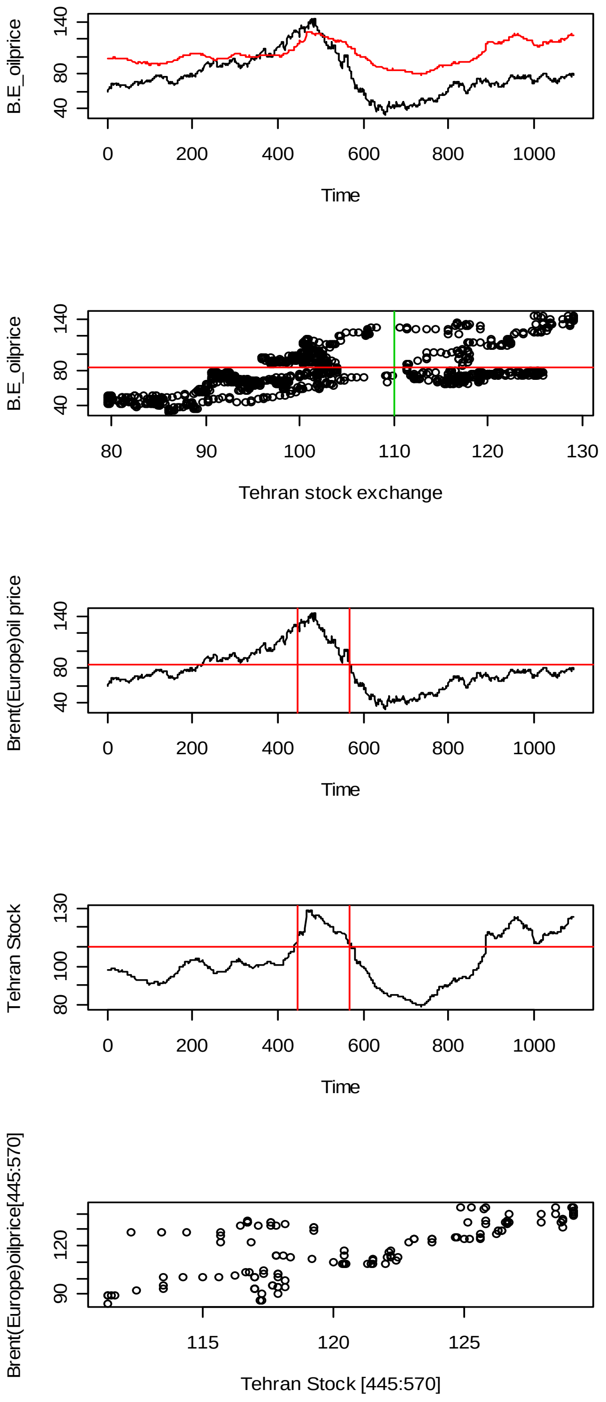
Note: In this figure, certain areas of the time series are investigated using the scatter plots to evaluate their correlation. Green line- plots values area separately. Red line- shows time periods in each series separately.

Figure 4.11: Plots of daily HHSP and EBSP time series.



Note: In this figure, certain areas of the time series are investigated using the scatter plots to evaluate their correlation. **Green line**- plots values area separately. **Red line**- shows time periods in each time series separately.

Figure 4.12: Plots of daily IDEX and EBSP time series.

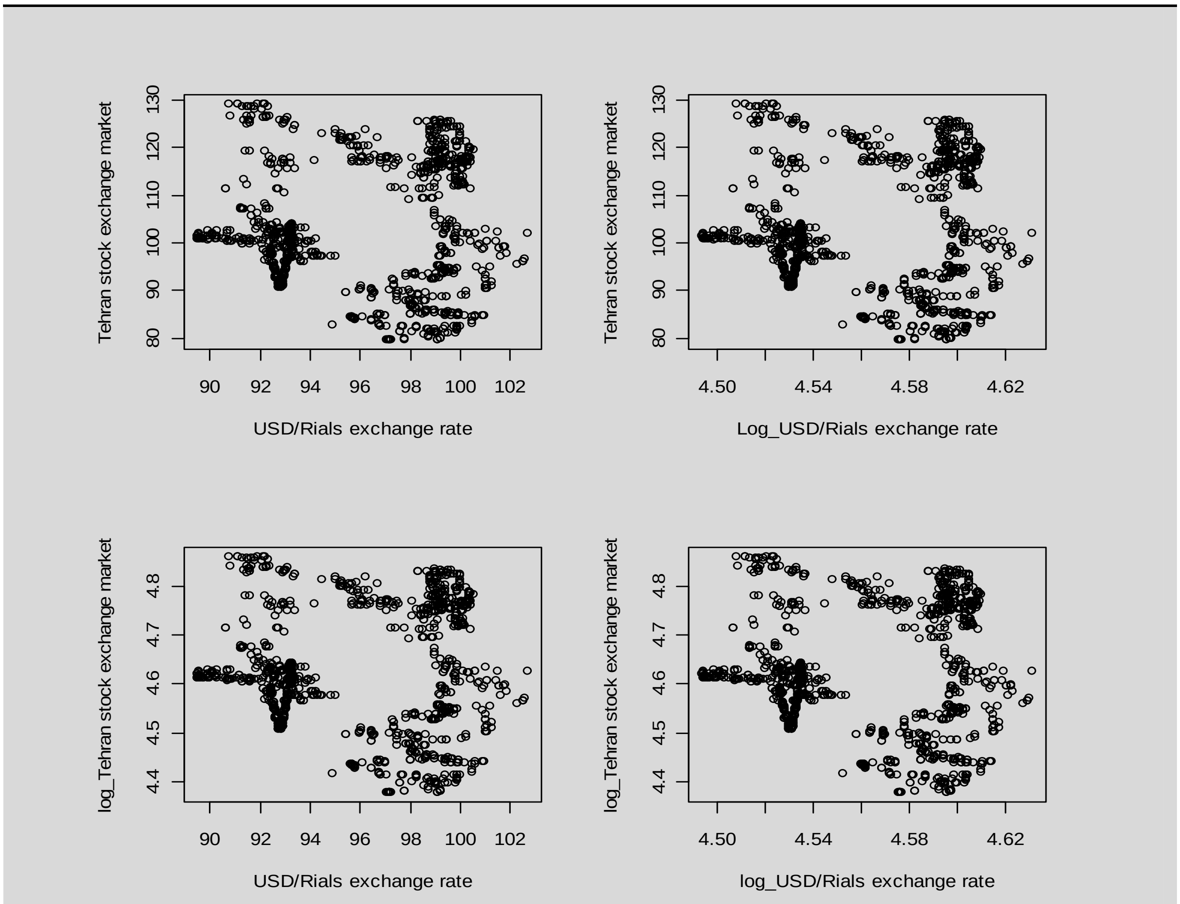


Note: In this figure, certain areas of the time series are investigated using the scatter plots to evaluate their correlation. **Green line**- plots values area separately. **Red line**- shows time periods in each time series separately.

Figure 4.13: Plots of daily TEPIX and EBSP time series.

As explained in Section 4.1, these four economic factors do not have any stationary behavior, which has led the researcher to consider the impacts of such behavior. This may change the accuracy of the evolving consideration of the relationship existing between time series (Hansen, 2012; Tsay, 2005; Donner & Barbosa, 2008). Logarithms may be used as a means of transformation in order to stabilize the variance of these time series (Tsay, 2005). But even after employing these logarithms, the results from the scatter plots in Figure 4.14 are the same as Figure 4.6. This implies that the different behavior of the variances in the times series do not mean they have an unusual role in these conflicted results.

Therefore, it may be the outliers which are most influencing the final results (Niven and Deutsch, 2012). In most of the scatter plots, the lines between the variables—the time series—were not exactly straight. In some parts, the plots in Figures 4.6 and 4.7 displayed densely-packed points in an oddly-shaped pattern. In other words, there are several points that may be considered outliers (Mitchell and Jolley, 2012; O'Rourke et al., 2005; Wolberg, 2006), so an examination of the role they play in the estimations is clearly justified.



Note: this figure uses the logarithms of the TEPIX, IDEX, HHSP and EBSP time series.

Figure 4.14: Scatter plot of pair of time series (after taking their logarithms).

4.1.1.C Robust correlation

The contradictory results achieved using Pearson's correlation coefficient measurements and scatter plots in the previous sections of this chapter raise the question that the relationships between the economic factors are sensitive to outliers. "Outliers can be loosely defined as observations which appear to deviate markedly from the other members of the sample" (Niven and Deutsch, 2012). This implies that the Pearson's correlation cannot be used to evaluate the robust measure of association between these two variables because its estimates may be affected by the presence of single outliers (Donner and Barbosa, 2008).

In general, correlation methods are useful with certain assumptions, such as our variables having a Gaussian (normal) distribution or their relationship and homoscedasticity of residuals (Hansen, 2012). The first assumption, of Gaussian distribution, is rejected in Figure 4.3 for all these economic factors, as there is "trimodal" behavior in the four time series histograms. Consequently, the robust method must be used, a method for computing the parametric correlation among variables. This can eliminate the requirements for the existence of a Gaussian distribution, not having the homoscedasticity of residuals and the existence of outliers in the time series (Hansen, 2012).

Niven and Deutsch (2012) postulated that "robust estimation of the means or covariance (and hence, the correlation) is to reduce the effect of outlier samples either by weighting or removing them altogether. The aim of robust methods is to ensure a high stability of statistical inference under the deviations from the assumed distribution model". This method has widespread applications, "because of the existence of the instability of classical methods due to the estimate of the presence of outliers in the data".

Gnanadesikan and Kettenring in 1972 explained that robust correlation is a natural approach to "robustifying" the sample correlation coefficient. It is used to replace the linear procedures of averaging by the corresponding nonlinear robust counter-sections (for more information refer to Shevlyakov and Smirnov, 2010).

Overall, there are different approaches to evaluating the correlation by the robust method, such as the Rousseeuw approach, which uses estimated correlation—and regression coefficients—by the least median of square (LMS). Gideon and Hollister employed the principle of maximum deviations in order to introduce a robust rank of correlation coefficients. Shevlyakov applied the Hampel medians of absolute deviations to achieve the median correlation coefficient in order to represent the robust correlation coefficient (see Niven and Deutsch, 2012). "The robust correlation method searches for ellipsoids that cover the "good section" of data" as opposed to the "bad" section, or outliers, in order to show the robust correlation of variables (Hansen, 2012).

This thesis uses a "robust method" based on the Rousseeuw approach in order to prepare a plot that draws an ellipse around the points contained in a classical correlation, and thus included in a robust calculation. In reality, the Least Median of Squares Regression (LMS) coefficients minimize the median of the squared residuals.

“One of the big advantages of LMS estimators is their noted 50% breakdown point, which means that LMS regression can give reliable results up to the point where 50% of the data are outliers” (Hansen, 2012; Shevlyakov and Smirnov, 2010).

Hence, the robust method is used in order to calculate the robust correlation between the time series, which is computed using the command cor.plot() function in the “mvoutlier” library of R (Hansen, 2012). In Figure 4.15, the robust correlation is compared against the classical correlation; see also Table 4.4.

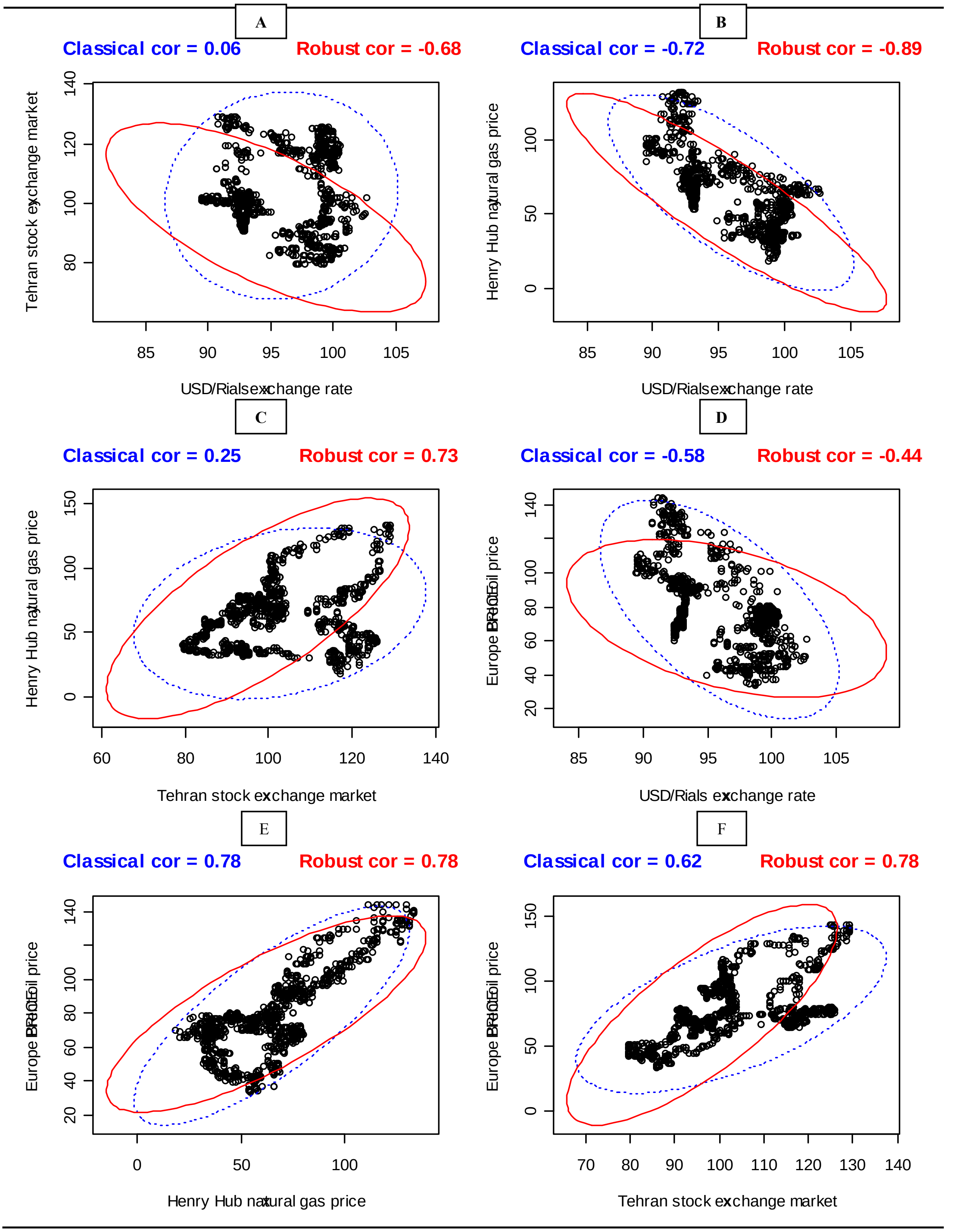
Several dense points in each scatter plot can be observed in Figure 4.15. This method treats these as outliers; here, there is an attempt to examine them using scatter plots to compare their behavior with the other points on the ellipse lines of the robust correlation method in the diagram related to each variable. The robust method results show the correlation is higher than in the classic methods used for each pair of factors. The only case where the correlation is shown to be less is between the IDEX and ESBP time series.

The classic correlation—or Pearson’s correlation measurement—between these economic variables, in this case the TEPIX and the IDEX, is very low in Figure 4.15-A and Table 4.4. However, in contrast with these results, there is clearly a high robust correlation between these two time series. This reoccurs between two other variables, the daily TEPIX and HHSP time series.

In addition, the robust scatter plots in Figure 3.15-B show that multicollinearity may be found between two of the independent variables, the daily IDEX and HHSP time series. It would be good to assume this condition in order to estimate their impact on Iranian electricity prices. Multicollinearity occurs when there is a linear relationship between two or more independent variables (Matt and Golder, 2014; Allison, 1999).

What is more, the robust scatter plots in Figure 4.15-C and D also proved the correlation between these two variables, the result of which shows a moderate degree of correlation, thus describing the spurious correlation between data. Finally, the robust scatter plots did not produce exactly straight lines between the time series either, the same as in Figures 4.6 and 4.7.

Table 4.5 raises the important issue that the results of robust methods using the Marazzi approach is different than those in Figure 4.15; see (R Documentation(CRAN), 2015). In this approach, “we compute a multivariate location and scale estimate with a high breakdown point – this can be thought of as estimating the mean and covariance of the good part of the data. cov.mve and cov.mcd are compatibility wrappers”(R Documentation(CRAN), 2015).



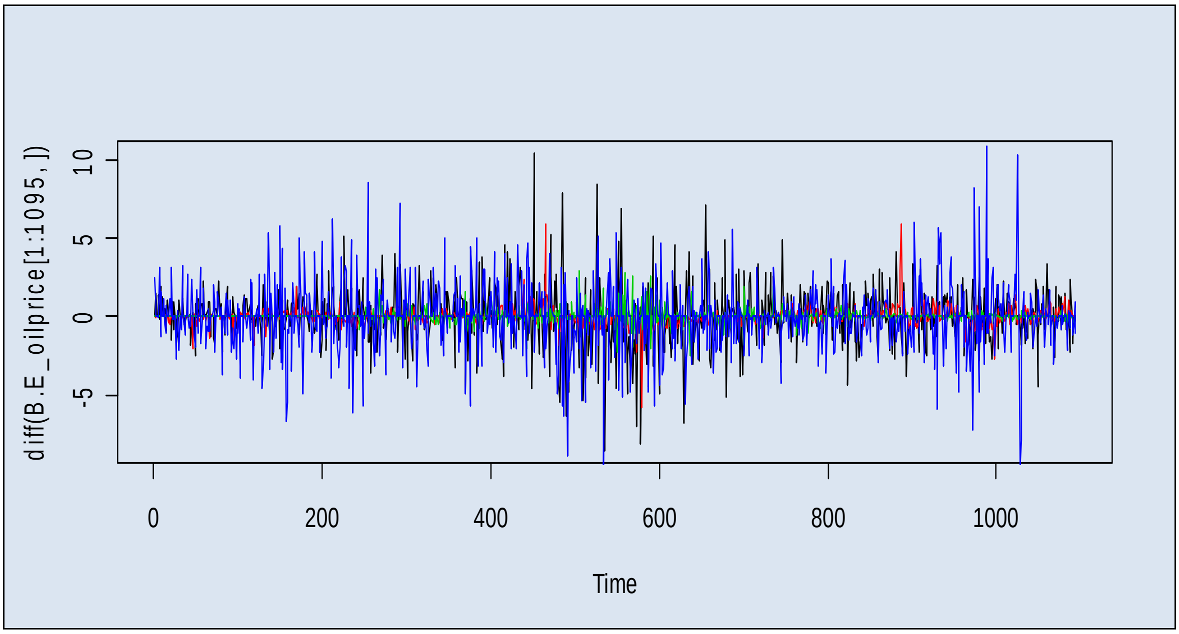
Note: Robust correlation scatter plot of the TEPIX, IDEX, HHSP and EBSP time series

Figure 4.15: Robust correlation scatter plot of the four economic factors.

Table 4.5: Robust correlation function results for our economic factors.

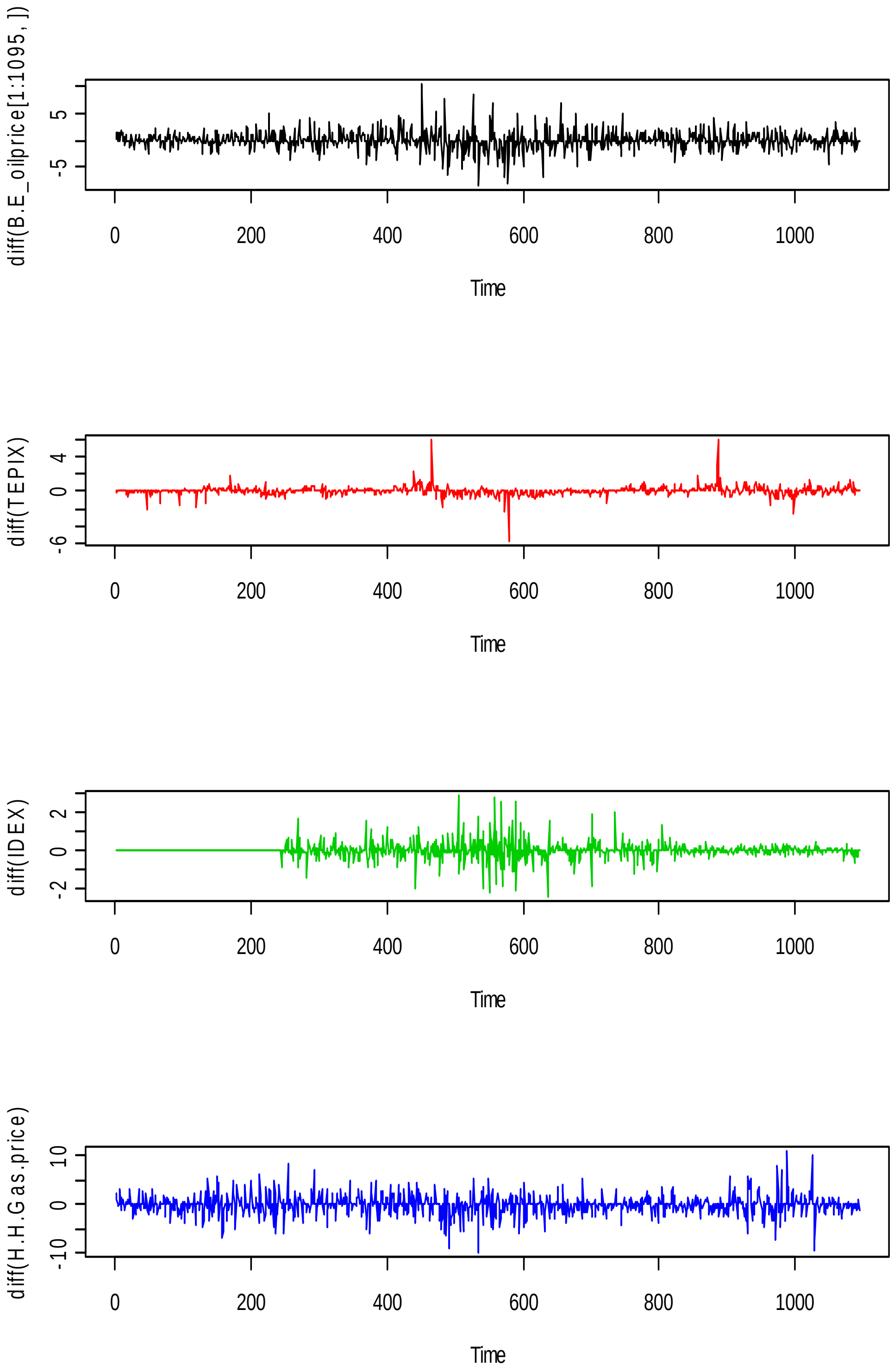
Robust Estimate of Correlation for				
R-code(40): covRob(data = index_v2.dat, corr = T)				
Time series	Daily HHSP time series	Daily TEPIX time series	Daily EBSP time series	Daily IDEX time series
Henry hub natural gas price time series	1.0000000	-0.7558337	0.3573757	-0.7502208
Tehran stock exchange price time series	-0.7558337	1.0000000	-0.1033241	0.9226112
Europe Brent oil price time series	0.3573757	-0.1033241	1.0000000	-0.1969720
USD/IRR exchange rate time series	-0.7502208	0.9226112	-0.1969720	1.0000000

Overall, these different and contradictory results have led the researcher to investigate the correlations of these pairs of time series after decreasing the non-stationary behavior in the time series; see Figures 4.16 and 4.17. This may be due to the non-stationary behavior creating complications in the estimation. However, in Figure 4.18, it is clear that there is no correlation or relationship between the factors, even after taking out the first-order differences.



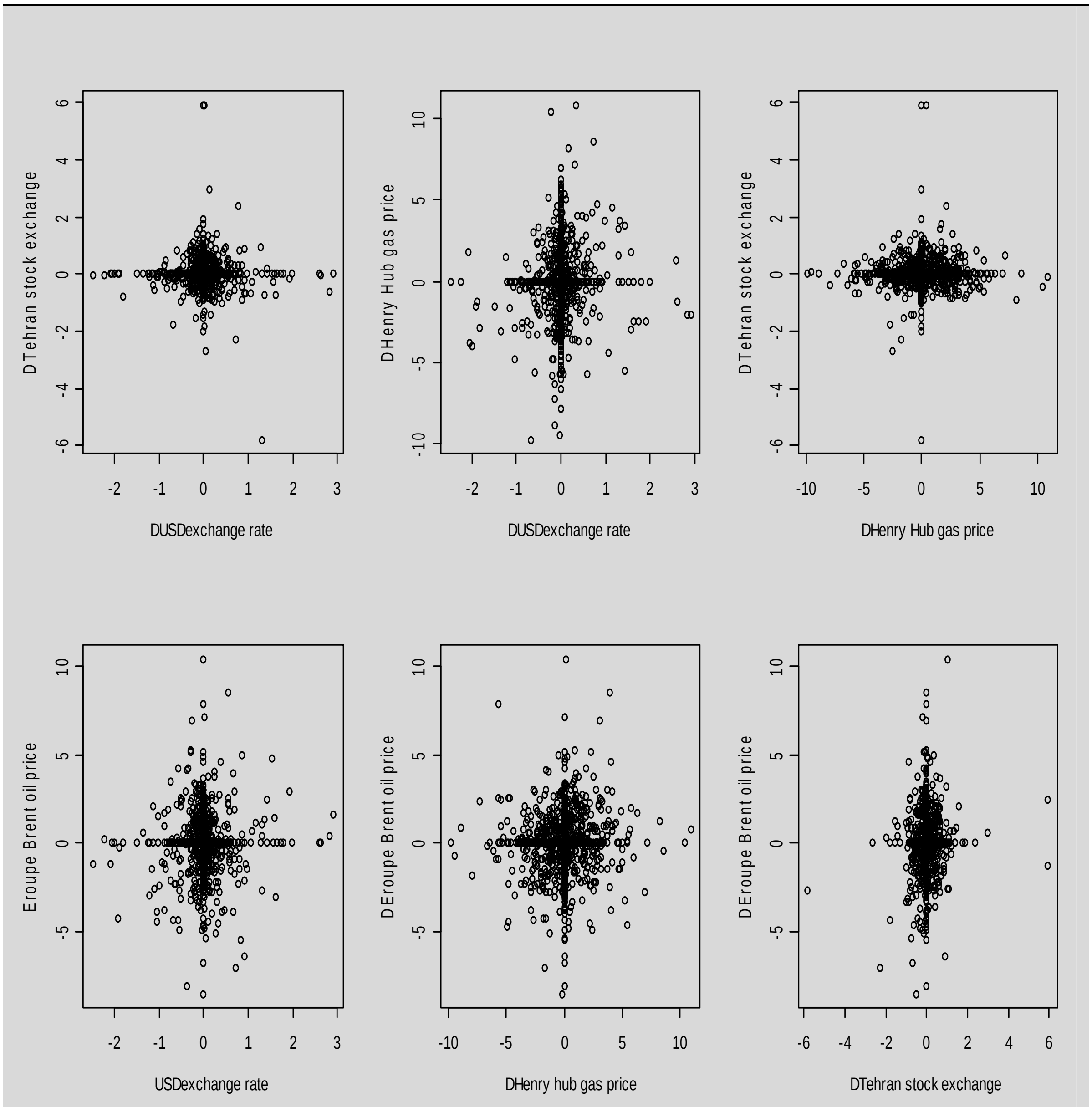
Note: **Red**- daily TEPIX, **green**- IDEX, **blue**- HHSP, **black**- EBSP time series.

Figure 4.16: Overlapping all economic factors / time series (after taking out differences).



Note: Red- daily TEPIX, green- IDEX, blue- HHSP, black- EBSP time series.

Figure 4.17: Comparison of time series plots (after taking out differences).



Note: The economic factors include time series of the daily TEPIX, IDEX, HHSP and EBSP.

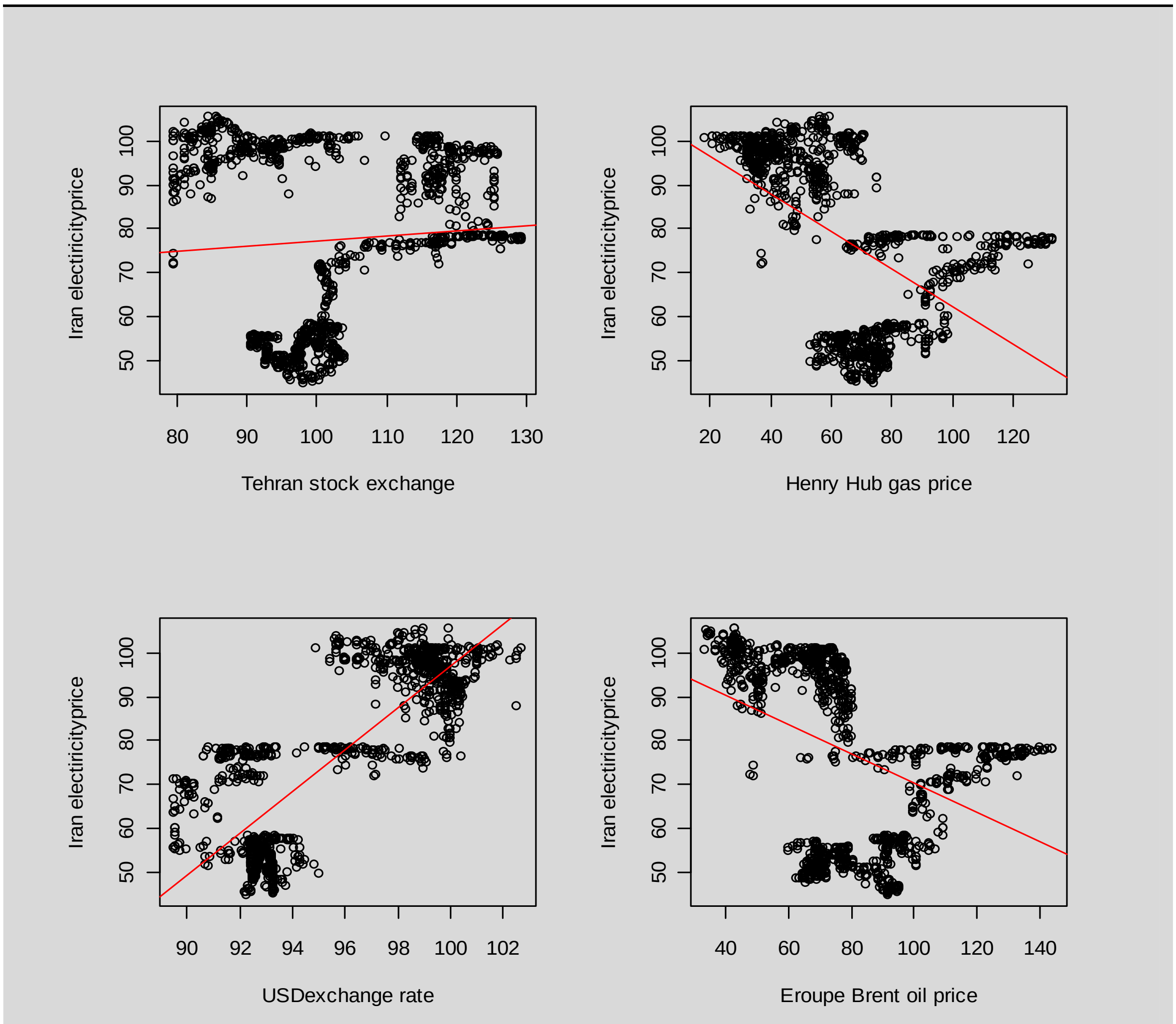
Figure 4.18: Scatter plot of pairs of economic factors
(after taking out first-order differences from their time series).

The results proves this main point, that no (linear) correlation and relationship exists between the economic factors (the daily Iranian-Tehran stock market price, the daily USD/IRR exchange rate, the daily Henry Hub natural gas price and the daily Europe Brent spot oil price). Hence, there is no possibility of estimating a (linear) regression model using these variables. Consequently, the investigation of their separate impact on the Iranian electricity price (IEP) time series may proceed, in search of the kind of relationship that does exist.

4.1.2 Investigating the relationship between Iranian electricity prices and the four economic factors

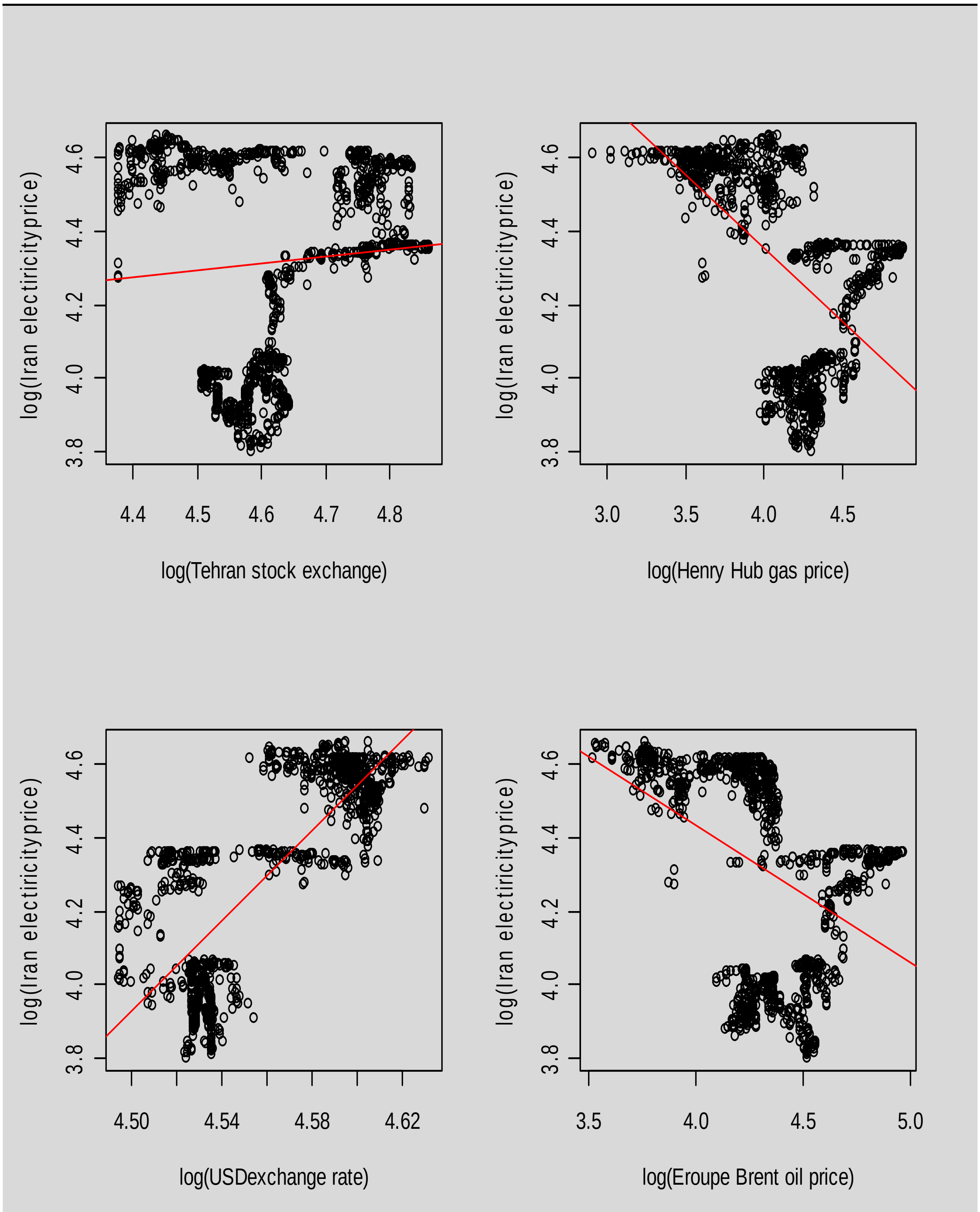
In general, the rate of market growth and deregulation can be usually be affected by the variations of economy factors. Some of these factors are energy prices such as oil prices or gas prices, the exchange rate, inflation, etc.

Therefore, this section will study the relationship between the IEP time series as a dependent variable and the previously mentioned economic factors, the daily TEPIX, IDEX, HHSP and ESBP time series, as independent variables.



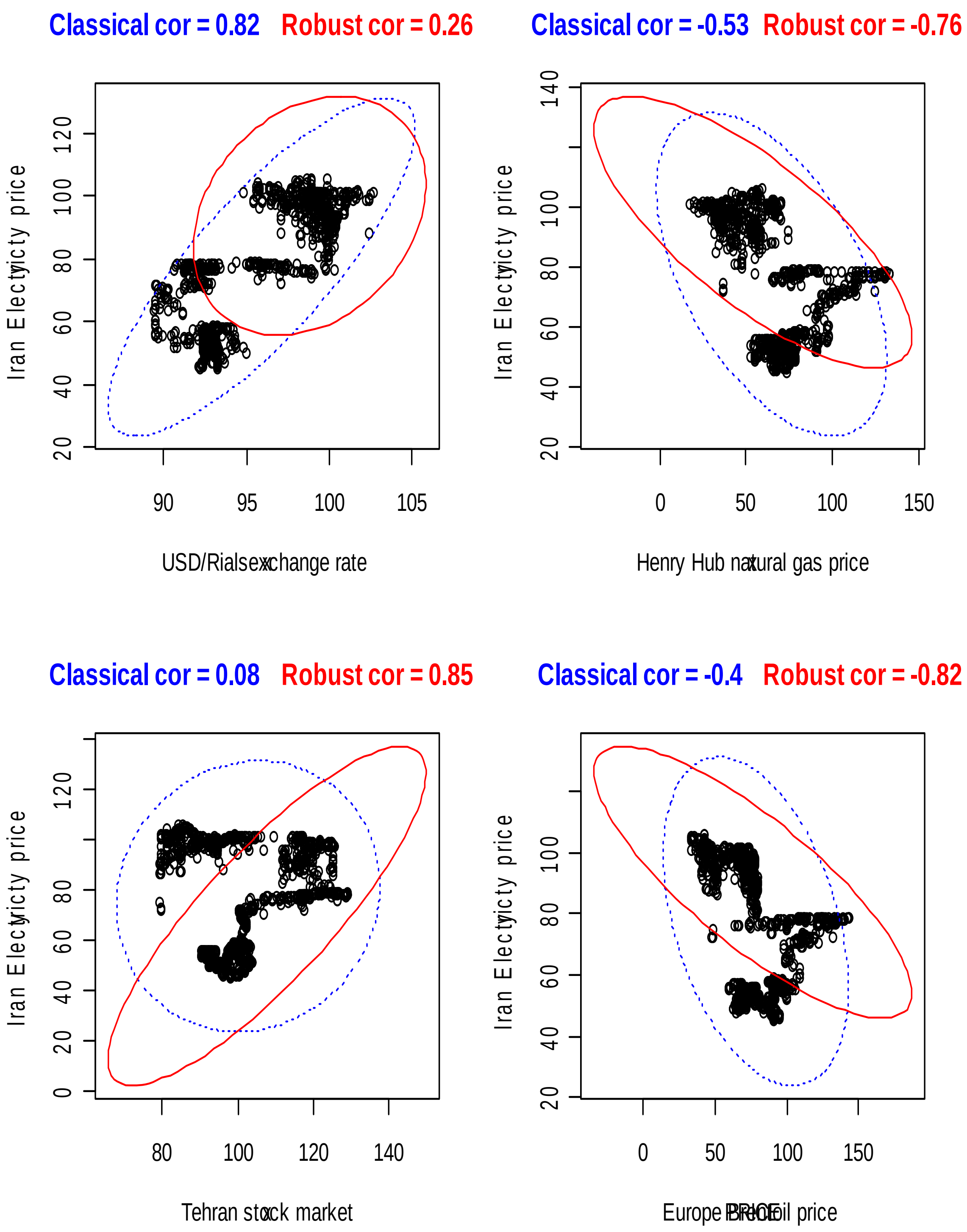
Note: The economic factors include time series of the daily TEPIX, IDEX, HHSP and EBSP.

Figure 4.19 : Scatter plot of the daily IEP and the four economic factors.



Note: The economic factors include time series of the daily TEPIX, IDEX, HHSP and EBSP.

Figure 4.20: Scatter plot of the daily IEP and the economic factors (after employing the logarithms).

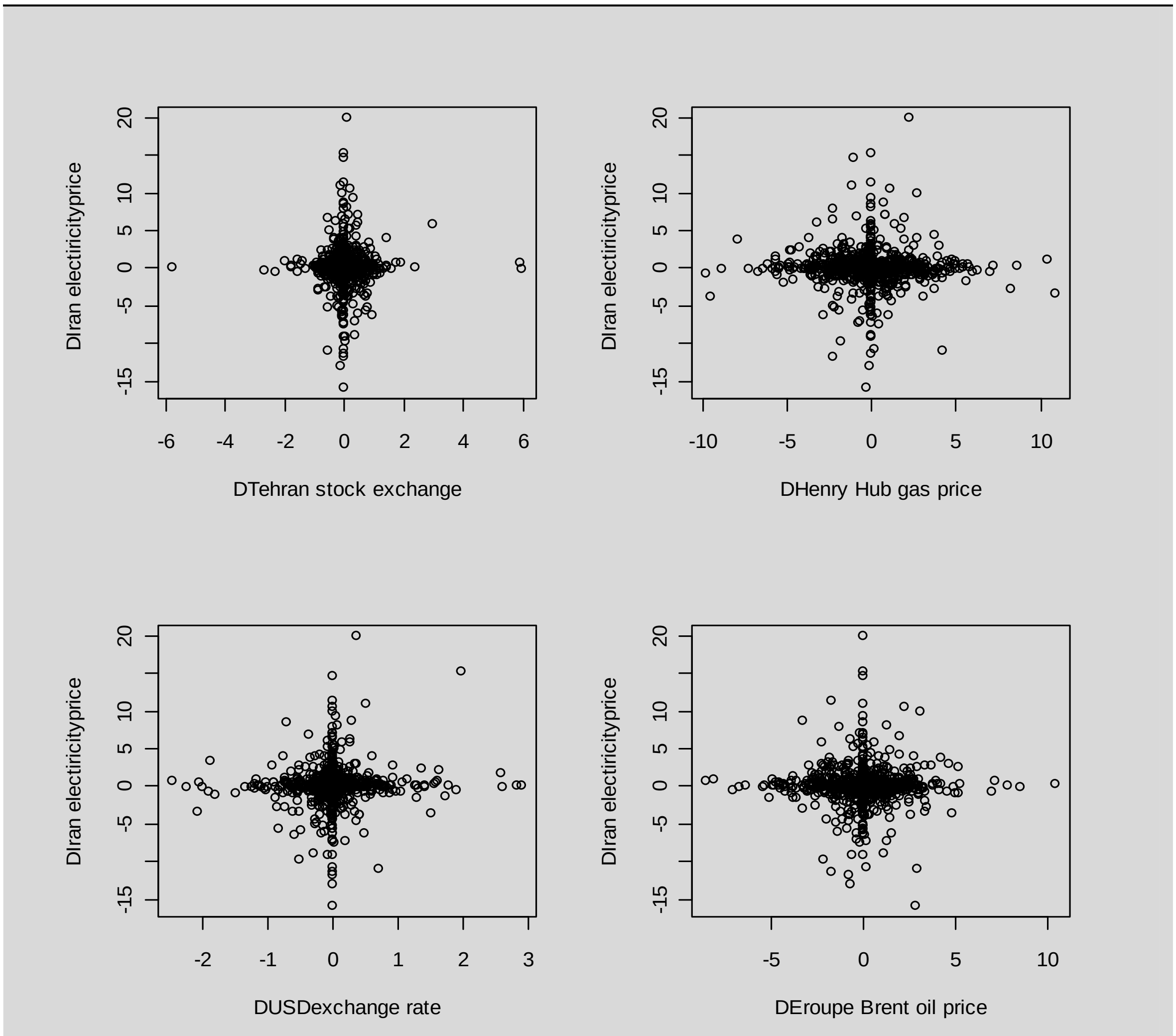


Note: The economic factors include time series of the daily TEPIX, IDEX, HHSP and EBSP.

Figure 4.21: Robust correlation scatters plot of the IEP and the four economic factors.

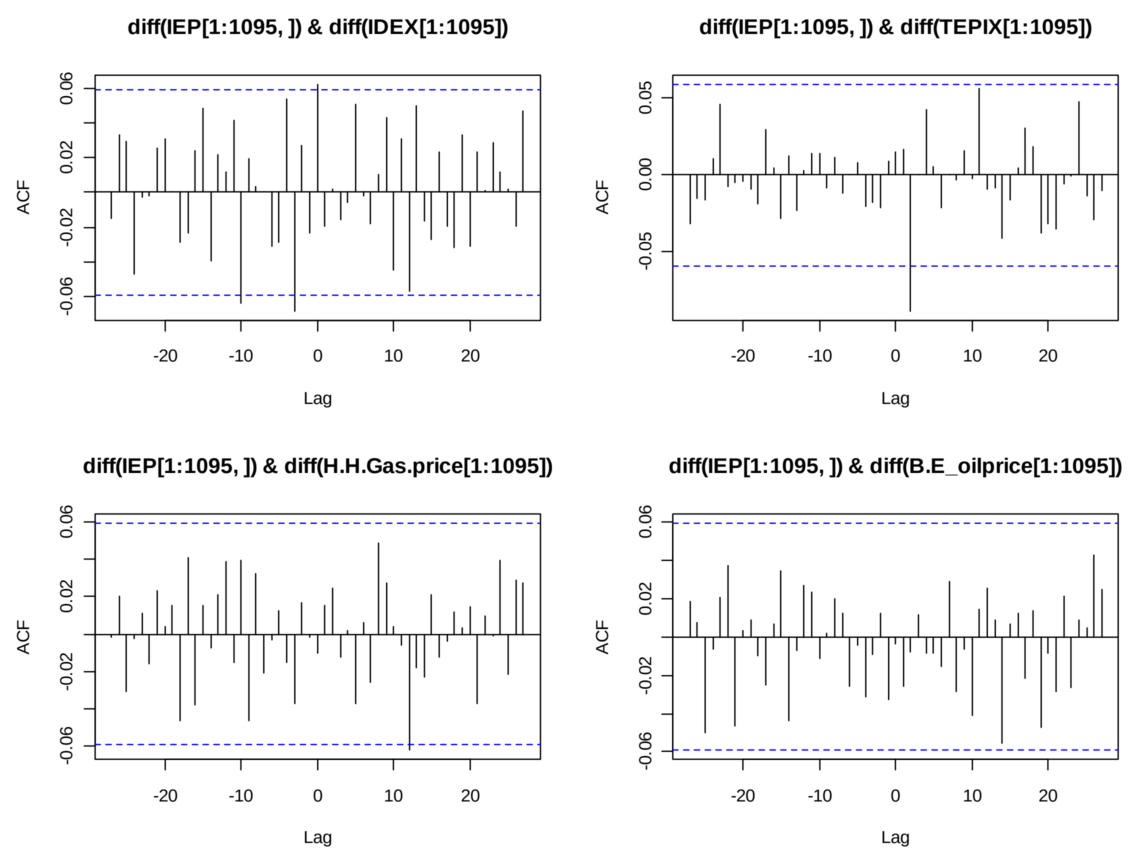
Table 4.6: Robust correlation function results of the IEP and the economic factors.

Robust Estimate of Correlation					
Time series	Iranian electricity price time series	Henry hub natural gas price time series	Tehran stock exchange price time series	Europe Brent oil price Time series	USD/Rialexchange rate time series
Iranian electricity price time series	1.0000000	-0.8352531	0.9230543	-0.2793531	0.9550842



Note: The economic factors include time series of the daily TEPIX, IDEX, HHSP and EBSP.

Figure 4.22: Scatter plots of the IEP time series and the economic factors (after taking out first-order differences).



Note: The economic factors include time series of the daily TEPIX, IDEX, HHSP and EBSP.

Figure 4.23: Cross-correlation functions of the IEP and the four economic factors.

All of the methods resulting in Figures 4.18-23 and Table 4.6 prove the absence of nonlinear/linear correlation and a relationship between the four economic factors and the IEP time series. Hence, there is no possibility of estimating a nonlinear/linear regression model for the IEP time series using these economic variables. This means that these economic indicators may not be the only factors having an impact on the progression the Iranian market.

Other factors such as international sanctions have redefined the Iranian economic market, especially in the energy sectors (Khalili and Mehri, 2007). The other important issue is the role the Iranian government plays as the main energy proprietor in the country's oil and gas industries (Cavendish and NA (Corporation), 2007; USA IBP, 2009). The Ministry of Energy dominates the electricity sector and determines the country's energy efficiency policy (Enerdata, 2014). In other words, economic factors do not particularly impact prices in the Iranian electricity market. Furthermore, these results suggest the study of the impact of other factors—such as political factors—on the Iranian electricity market in future research.

4.2 Forecasting via simulation

It is well known that electricity price forecasting is helpful for market operators, particularly power generating companies who must manage their units and the associated economic risks (Benini, et al., 2002). In 2012, Vilar et al. explored electricity demand and price forecasting in the competitive Spanish electric power market. Electricity price forecasting is also extremely important for all market players in the short, medium and long term (Benini, et al., 2002). In addition, basic economic theories explain that the pattern of price via demand is predictable in competitive markets (Nicholson and Snyder, 2011).

As explained in Chapter 3, no relationship between price and load could be established in Iranian electricity market. Therefore, in order to find out more strategic knowledge about this market, the researcher has decided to present a separate forecast for price and load. This also leads to a comparison of these results with a forecast of the Spanish electricity market. These predictions will be useful in learning the behavior of price and load as important elements in both these markets. The kind of forecast that this thesis presents covers approximately a 14-day period.

In this section, the GSgarch.Sim() function of the 'GEVStableGarch' package in R will be utilized to simulate or forecast the time series following the ARMA-GARCH models in several conditional distributions, including GEV and stable distributions (for more detail, see do Rego Sousa et al., 2014).

R-code (40): To employ the GSgarch.Sim function in order to simulate the ARMA-GARCH model for Spanish electricity price through the GEV and stable conditional distributions.

```
source("GevstableGarch.r")
spainElectricityprice.sim1<-GSgarch.Sim(N =20, mu =0,a=0.56609, b=c(0.16438,0.15253,0.14561,0.15653,0.14545,0.14131,-0.74835),omega=0.03910, alpha =0.06997, beta =0.92805 ,skew = 0, shape = 3, cond.dist = "std")
summary(spainElectricityprice.sim1)
```

For the Iranian electricity price (IEP), an out-of-sample prediction will be made using the fourth part of the ARMA-TGARCH model in Table 4.7-D. For the Spanish electricity price (SEP), an out-of-sample prediction will be put forth according to the ARMA-GARCH model in Table 4.7-F. The out-of-sample prediction for Iranian and Spanish electricity load (IEL and SEL) will utilize the ARMA-GARCH models Table 4.7-E and Table 4.7-G, as it is the best of estimated model for these markets (see Chapter Three).

The prediction of the IEP is presented in Figure 4.24. This daily forecasting was performed from the 1082nd to the 1095th day of the sample. The sample forecasting has a very similar behavior to the real observation, and falls within a confidence intervals of 95%, as seen in Figure 4.24 and Table 4.8.

Table 4.7: Statistical equation of best models
– The estimation models for forecasting the Iranian and Spanish electricity markets.

ARMA-TGARCH model	For Iranian electricity price time series.
A- For first section ARMA-GARCH model	$r_t = a_t - 0.2641948\,a_{t-1}$ $a_t = \sigma_t \varepsilon_t$ $\sigma^2 = 0.029284 + 0.1203102\,\varepsilon^2{}_{t-1} + 0.8361440\,\sigma^2{}_{t-1}$
B-For second section ARMA-GARCH model	$r_t = a_t - 0.28762\ a_{t-1}$ $a_t = \sigma_t \varepsilon_t$ $\sigma_t^2 = 0.08819 + 0.45640\ \varepsilon^2{}_{t-1} + 0.54072\ \sigma_{t-1}^2$
C-For third section ARMA-GARCH model	$r_t - 0.6563\ r_{t-1} = a_t - 0.76807\ a_{t-1}$ $a_t = \sigma_t \varepsilon_t$ $\sigma_t^2 = 0.12611\ \varepsilon^2{}_{t-1} + 0.83328\ \sigma_{t-1}^2$
D- For fourth section ARMA-GARCH model	$r_t = -0.05686 + a_t - 0.30447\ a_{t-1}$ $a_t = \sigma_t \varepsilon_t$ $\sigma_t^2 = 0.27724\ \varepsilon_{t-1}^2 + 0.64223\ \sigma_{t-2}^2$
ARMA-GARCH model	For Iranian electricity load time series.
E- ARMA-GARCH model	$r_t - 0.68302\,r_{t-1} + 0.022227\,r_{t-2} = a_t - 0.877191\,a_{t-1} - 0.661868\,a_{t-7} - 0.5942\,a_{t-8}$ $a_t = \sigma_t \varepsilon_t$ $\sigma^2 = 6.6034 + 0.1935\,\varepsilon^2 + 0.768\,\sigma^2{}_{t-1}$
ARMA-GARCH model	For Spanish electricity price time series.
F- ARMA-GARCH model	$r_t - 0.566\,r_{t-1} = a_t - 0.164\,a_{t-1} - 0.152\,a_{t-2} - 0.145\,a_{t-3} - 0.156\,a_{t-4} - 0.145\,a_{t-5}$ $-0.141\,a_{t-6} + 0.748\,a_{t-7}$ $a_t = \sigma_t \varepsilon_t$ $\sigma^2 = 0.0391 + 0.0699\,\varepsilon^2 + 0.92805\,\sigma^2{}_{t-1}$
ARMA-GARCH model	For Spanish electricity load time series.
G- ARMA-GARCH model	$r_t + 0.4191 r_{t-1} = a_t - 0.346 a_{t-1} - 0.333 a_{t-2} + 0.336 a_{t-3} + 0.333 a_{t-4} + 0.3249 a_{t-5} + 0.3244 a_{t-6} - 0.618 a_{t-7}$ $a_t = \sigma_t \varepsilon_t$ $\sigma^2 = 80.26 + 0.29312\varepsilon^2 + 0.5704\sigma^2{}_{t-1}$

Table 4.8: Forecasting the IEP in comparison with the real electricity price.

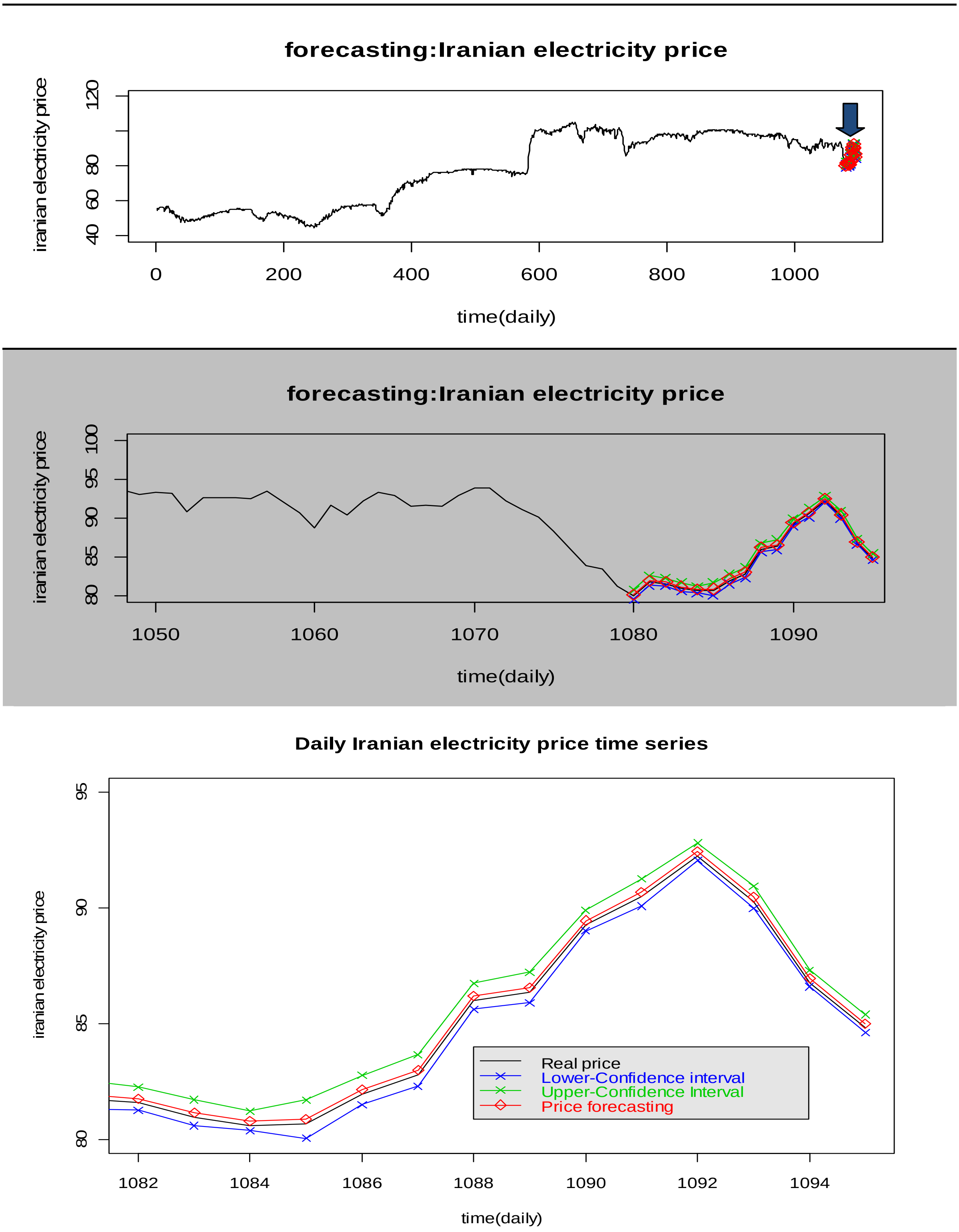
	The Real observations	With 95% confidence intervals		Forecast for Iranian electricity price	Sigma.t
		Lower	Higher		
1	81.56781	81.24997	82.26366	81.75682	0.2534226
2	80.95916	80.58654	81.70980	81.14817	0.2808174
3	80.60204	80.37540	81.20670	80.79105	0.2078269
4	80.68095	80.04239	81.69753	80.86996	0.4137868
5	81.94573	81.50202	82.76746	82.13474	0.3163592
6	82.78838	82.29686	83.65792	82.97739	0.3402650
7	85.99574	85.62736	86.74214	86.18475	0.2786931
8	86.37161	85.90235	87.21889	86.56062	0.3291373
9	89.26797	89.00455	89.90941	89.45698	0.2262134
10	90.47931	90.07833	91.25831	90.66832	0.2949969
11	92.24470	92.06301	92.80441	92.43371	0.1853487
12	90.27382	89.98064	90.94502	90.46283	0.2410941
13	86.75947	86.59141	87.30555	86.94848	0.1785345
14	84.81760	84.61887	85.39435	85.00661	0.1938721

A forecast was also made for the IEL, which is shown in Figure 4.25; once again, it has a very similar pattern to the real data. The predictions are observed to be within the confidence intervals at a level of 95%; see Figure 4.25 and Table 4.9. The daily IEL forecasting was performed from the 1075th to the 1086th day of the sample.

The comparison of the behavior of price and load in Figures 4.24 and 4.25 clearly indicate that the patterns of these two components in the Iranian electricity market are mostly different. This result again proves that no kind of relationship exists between the IEP and IEL. In other words, the pattern of price via demand cannot be predicted in Iranian electricity markets.

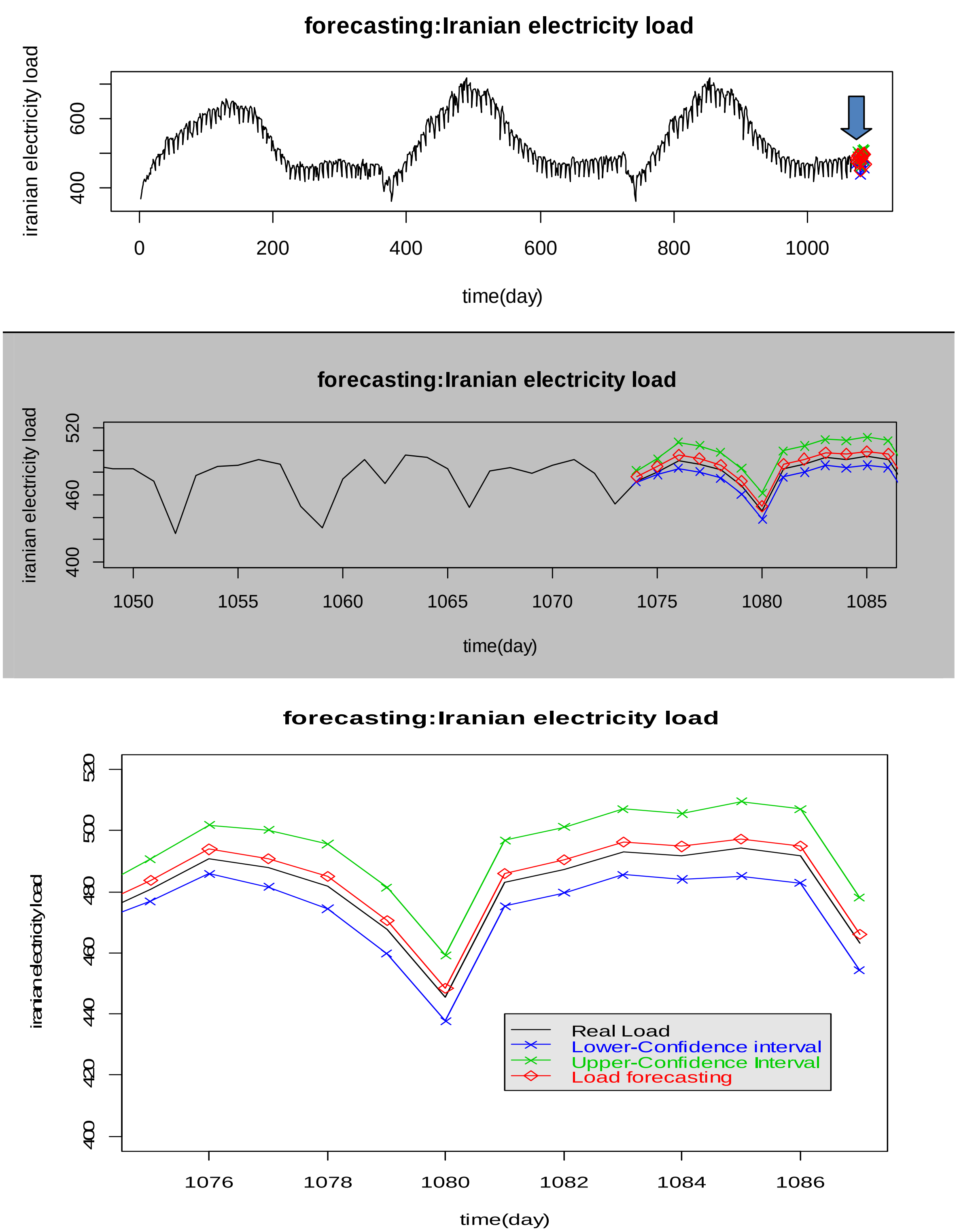
Table 4.9: Forecasting the IEL in comparison with the real electricity load.

The observations		With 95% confidence intervals		Forecast for Iranian electricity load	Sigma.t
		Lower	Higher		
1	471.8201	467.6851	483.1927	475.4389	2.584601
2	480.7321	473.7897	494.9121	484.3509	3.520396
3	490.8253	482.3903	506.4977	494.4440	4.017899
4	487.7994	477.5297	505.3066	491.4181	4.629473
5	481.9531	470.7973	500.3464	485.5719	4.924855
6	467.5351	456.0791	486.2287	471.1539	5.024942
7	445.4192	433.7256	464.3503	449.0379	5.104122
8	483.0048	466.1189	507.1281	486.6235	6.834856
9	487.3572	468.4657	513.4862	490.9760	7.503422
10	493.2219	475.6272	518.0541	496.8407	7.071147
11	491.7683	474.5096	516.2644	495.3870	6.959135
12	494.2757	477.9595	517.8294	497.8944	6.644986
13	491.9229	476.3429	514.7403	495.5416	6.399565
14	463.1368	442.8941	490.6170	466.7556	7.953809



Note: Red points in the figures show forecasting, the black line the real price and the green and blue lines show the confidence intervals.

Figure 4.24: Forecasting the IEP (for 14 days).



Note: Red points in the figures show forecasting, the black line the real load and the green and blue lines show the confidence intervals.

Figure 4.25: Forecasting the IEL (for 14 days).

Table 4.10: Forecasting the SEP in comparison with the real electricity price.

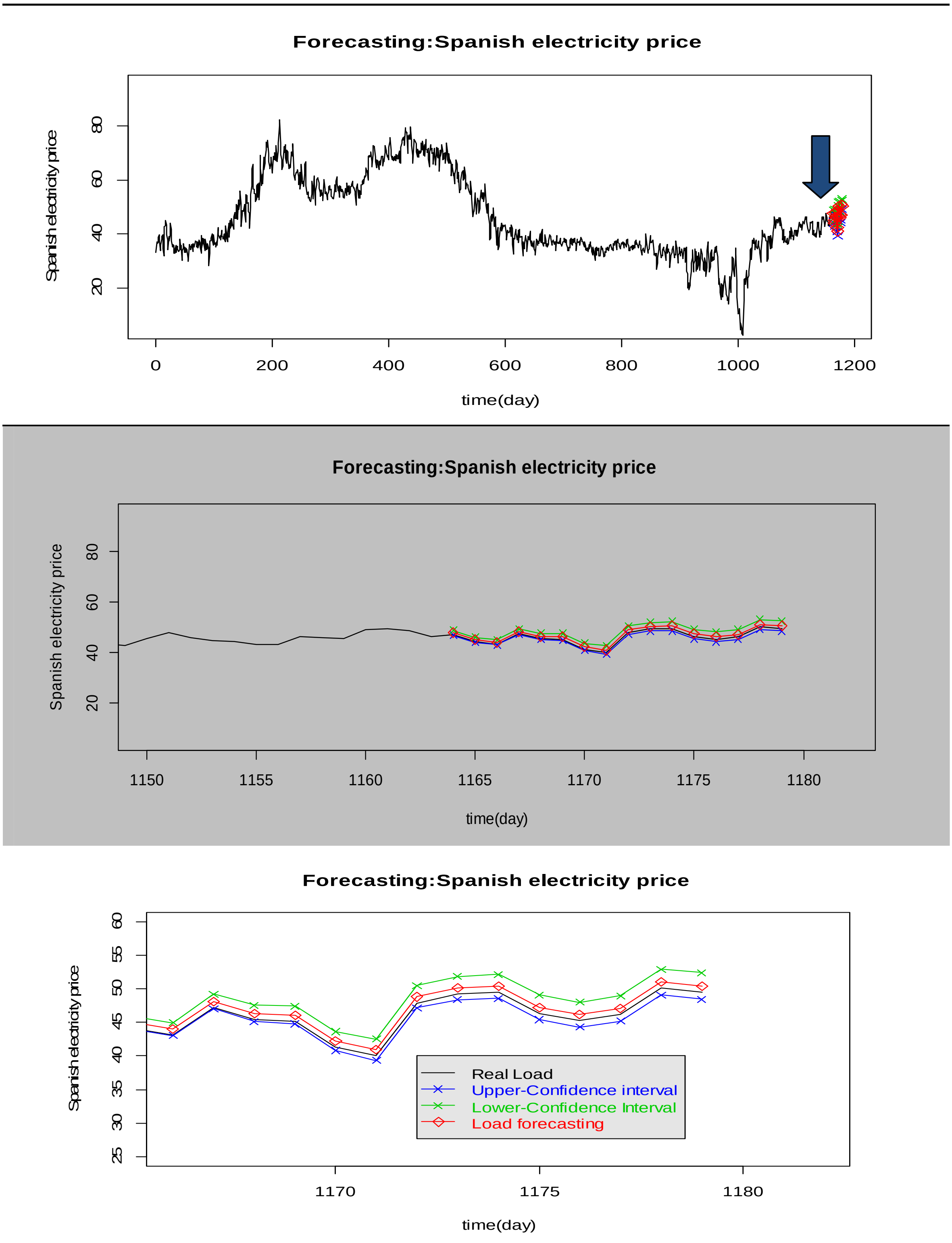
The observations		With 95% confidence intervals		Forecast for Spanish electricity price	Sigma.t
		Lower	Higher		
1	43.081	43.04284	44.94020	43.99152	11.24139
2	47.244	47.06496	49.24408	48.15452	12.74555
3	45.455	45.14589	47.58515	46.36552	13.15140
4	45.192	44.78632	47.41872	46.10252	13.64088
5	41.324	40.83465	43.63439	42.23452	14.25369
6	40.030	39.33211	42.54893	40.94052	19.75873
7	47.916	47.15900	50.49404	48.82652	22.38770
8	49.223	48.41203	51.85501	50.13352	27.24621
9	49.487	48.60653	52.18851	50.39752	22.89371
10	46.350	45.43581	49.08523	47.26052	19.47490
11	45.241	44.29624	48.00680	46.15152	18.01179
12	46.190	45.21610	48.98494	47.10052	19.07852
13	50.125	49.12092	52.95012	51.03552	18.95453
14	49.528	48.46924	52.40780	50.43852	26.73247

The forecasting of the SEP is found in Figure 4.26, where the predictions are also observed to be within the confidence intervals at 95%; see Figure 4.26 and Table 4.10. In other words, the real data was found to behave similarly to the forecast, which was performed from the 1166^{th} to the 1179^{th} day of the sample.

As for the SEL, its forecast is given in Figure 4.27, where the predictions again fall within the same confidence intervals; see in Figure 4.27 and Table 4.11. This means the forecast acts in the same way as real data. This daily forecasting was performed from the 1174^{th} to the 1187^{th} day of the sample. Figures 4.24 and 4.25 indicate that the SEP and SEL have the same pattern of behavior, pointing toward the existence of a relationship between price and load in the Spanish electricity market (see Chapter 3).

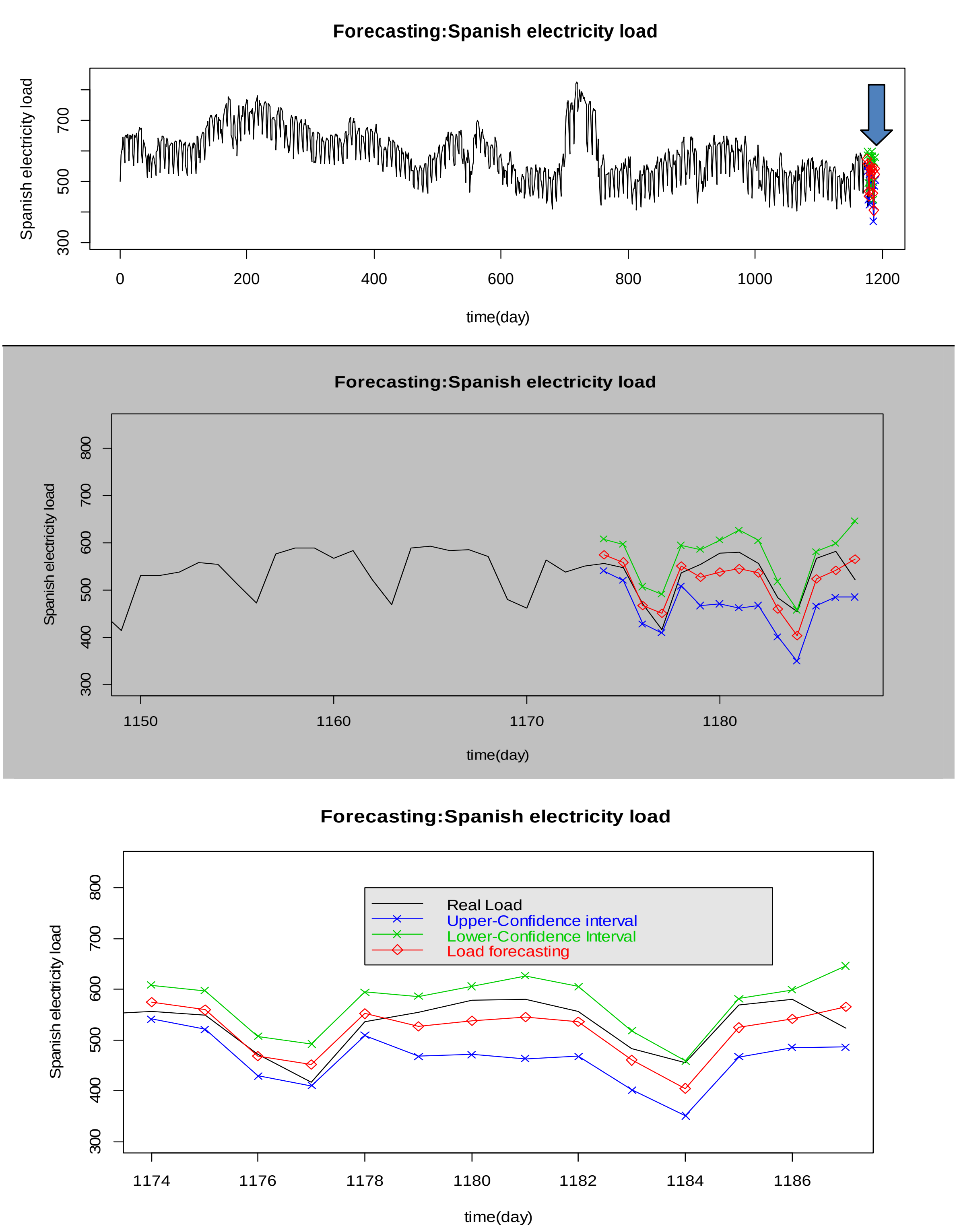
Table 4.11: Forecasting the SEL in comparison with the real electricity load.

The observations		With 95% confidence intervals		Forecast for Spanish electricity load	Sigma.t
		Lower	Higher		
1	556.607	540.9025	608.3508	574.6266	11.24139
2	548.181	521.0010	597.4743	559.2376	12.74555
3	471.692	428.8414	507.7498	468.2956	13.15140
4	416.418	410.2680	492.1133	451.1906	13.64088
5	535.994	509.1036	594.6257	551.8646	14.25369
6	554.105	467.7034	586.2558	526.9796	19.75873
7	577.868	471.5435	605.8697	538.7066	22.38770
8	579.531	463.2010	626.6783	544.9396	27.24621
9	557.059	467.8325	605.1948	536.5136	22.89371
10	483.434	401.5999	518.4493	460.0246	19.47490
11	454.832	350.7153	458.7860	404.7506	18.01179
12	568.455	467.0911	581.5622	524.3266	19.07852
13	581.194	485.5740	599.3012	542.4376	18.95453
14	522.899	486.0032	646.3980	566.2006	26.73247



Note: Red points in the figures show forecasting, the black line the real price and the green and blue lines show the confidence intervals.

Figure 4.26: Forecasting the SEP (for 14 days).



Note: Red points in the figures show forecasting, the black line the real price and the green and blue lines show the confidence intervals.

Figure 4.27: Forecasting the SEL (for 14 days).

Overall, these results indicate that the estimated models for electricity price and load are highly suitable for determining the behavior of price and load in both the Iranian and Spanish electricity markets. The findings of this chapter provide strategic knowledge and better estimates regarding these energy markets, so rapid market changes that occur can be taken into account in future planning.

Chapter Five: Conclusions and Further Research

5 Conclusions

The main objective proposed for this thesis has been fulfilled; an in-depth investigation has been made into the impact of effective factors on the Iranian electricity market in comparison with the Spanish electricity market. Each chapter has addressed the main questions posed by this study that had been enumerated in the first chapter. According to the new interpretations of Article 44 of the previously cited Iranian law, the Iranian government aim to turn its market into a "free" market. This research is of great use to understanding exactly how Iranian market mechanisms work after some of its dimensions have fundamentally progressed; in particular, these refer to molding the rapid growth in technical infrastructure and expanding the privatization laws governing this market.

This thesis attempted to address whether or not the Iranian electricity market can be categorized as a competitive and liberalized market. With this goal in mind, a comparison was made to that of Spain. A time series approach to employing linear and non-linear models was presented, with price and load being the main factors in each of these markets. In determining the role load played in these markets, an association between load and price was discovered. However, it was further suggested that such a relationship is by no means significant in the Iranian electricity market.

This conclusion motivated the researcher to answer the question of whether other main macro and microeconomic indicators might be influencing the Iranian energy market—factors such as the USD/IRR exchange rate, the Tehran stock exchange price, the Henry Hub natural gas spot price and the European Brent oil spot price. The results of this part of the research was that these indices, much as it was with load, had no significant bearing on the price of electricity. It was also determined that it would be fruitful for future research to investigate the impact of other, more political factors, such as the Iranian government's strategies regarding international embargoes. In addition, the importance of forecasting in energy market policies indicated the need to perform short-term predictions for each index: Iranian and Spanish electricity prices and Iranian and Spanish electricity loads. These forecasts employed the most suitable models derived from the research and also clearly indicated the different behavior patterns of these indices might have in a future Iranian electricity market.

Briefly, the conclusions reached in third and fourth chapters are based on the survey of four time series: Iranian electricity prices (IEP), Spanish electricity prices (SEP), Iranian electricity loads (IEL) and Spanish electricity loads (SEL). There also was an in-depth examination of the Iranian electricity market in order to compare it with the Spanish electricity market (MIBEL) as a developed market. These market analyses were based around the search for a valid model for each time series using different modelling approaches, such as the ARIMA and SETAR models, the ARMA-TGARCH, ARMA-GARCH and SARMA-SGARCH models, etc.

In these time series analysis models, it was revealed that there is a seasonal impact the process of estimating a valid model in the IEL, SEP and SEL time series. In addition, the analysis of established estimation models (such as ARIMA) for these four indices proved volatility and serial correlation play a significant role in each time series, suggesting the influence of other factors on these energy markets. For example, the research into Spanish electricity prices demonstrated that wind power tends to influence market prices. This is why the ARMA-GARCH models, also known as heteroskedastic time series models, were developed and further verified using the Mean Square Error tests to estimate the behavior of the IEL, SEP and SEL.

Unlike the Spanish electricity market, analysis suggests that the IEP exhibits a fully non-linear behavior, which is confirmed by the existence of break points and structural changes in the data trends. Therefore, in contrast to the Spanish market, the IEP time series must be estimated by an ARMA-TGARCH model. Several ARMA-GARCH models were also used to accurately forecast price/load, taking into account the nonlinear behavior patterns in the market. Similar patterns were also demonstrated in the SEL and IEL time series, since the IEL is also modelled using an ARMA-GARCH. However, in the Spanish electricity market, both indices (price and load) followed a similar pattern and could be estimated by the ARMA-GARCH models. This investigation concluded that the Iranian and Spanish electricity markets exhibit a fundamental difference concerning the behavior of their respective load and price time series.

The third chapter also investigated the relationship between price and load in these two markets. The results strongly suggested that the rate of load does not influence the Iranian electricity market price in any meaningful way. Furthermore, the scatter plots and cross correlation function diagrams of all four time series pointed towards the fact that, unlike Spain, not only is there no clear relationship between load and price in the Iranian market, the existence of any meaningful dependency on price volatility and load can also be rejected. In contrast, the Spanish electricity market was examined using the "Rational Distributed Lag" model with SAS. In this ARIMAX model, the daily SEP was estimated as output, while load and the electricity generated by wind power were estimated as inputs. The residuals analysis concluded that the SEL and wind power indeed have an impact on prices in this market.

The fourth chapter dealt with a market analysis of the impact of other micro and macroeconomic factors on pricing in the Iranian electricity market. In this study, it was proven that certain economic factors, such as the USD/IRR exchange rate, the Tehran stock exchange, Henry Hub gas spot price and the European Brent oil spot price, do not have a significant impact on the Iranian electricity market or its prices. Scatter plots and other time series statistical methods indicated the lack of any real relationship between the IEP and these four factors.

In another section of the same chapter, the importance of forecasting in electricity market policies led the researcher to perform short-term out-of-sample predictions for each of market factor. This utilized the most suitable models previously determined in the thesis for predicting the behavior of future Iranian and Spanish electricity prices and loads. Furthermore, these predictions also clearly showed the different patterns between these indices—price and load—in the Iranian electricity market. The forecasts also suggested crucial factor such as loads do not affect the price in the Iranian market. In contrast, the patterns of price and load in the Spanish electricity market are similar to one another when projected into the future. In other words, load does haves an effect on pricing strategies in a developed electricity market, which is Spain's.

These results prove fairly the mechanisms of the Iranian and Spanish electricity markets have nothing in common. Meanwhile, in consideration of the modelling and analysis performed on both markets, the Iranian electricity market can be recognized as a non-free/centralized market.

Furthermore, this calls into question the policies thus far implemented toward decentralizing and privatizing the Iranian market.

In order to take any meaningful steps towards constructing a free market, potential reforms need to be implemented by policy makers. These cannot be limited to only technological improvements; they must address the current challenges facing Iran and the Iranian market, i.e., international sanctions, the Iranian political economy, the inflation rate, and law-making policies. A good start would be the research into the impact of other micro and macroeconomic factors on the dynamics of the Iranian electricity market.

5.1 Further Research

Considering the research done thus far, it would be worthwhile investigating other potentially influential factors acting within the Iranian electricity market, such as the role of nuclear, coal and wind as other energy recourses in this market and also other micro and macroeconomic factors, like GDP growth and interest rates, the rate of inflation rate, etc., as well as political factors such as the government's strategies regarding international embargoes. On the other hand, although this thesis was able to characterize the differences in the both markets however it will be fine to have more success in identifying the causal mechanism in these markets. In other words, decision makers would benefit from exploring the role of other issues in their energy policy.

This researcher also suggests decision makers analyze the structure of the Iranian electricity market using other statistical approaches in time series analysis. The further suggestion for next studies is to consider using Bayesian dynamic models in time series analysis, particularly the Mike West modelling approach, as these are driven by latent factor models (see West, (2013) and Petris et al., (2007)).

Considering the Spanish and Iranian electricity markets is shown that the Iranian electricity market can be recognized as a non-free/centralized market. This Iranian electricity market mechanism can lead us to compare this market with Spanish electricity market of 20 years ago.

Market analysis would stand to benefit greatly from other dimensions, such as investigating the quality of the management structure systems, surveying the existence of a renewable energy policy for this market, evaluating retail market structures, etc.

5.2 Publications and presentations generated by this thesis

Conference and publication

Nasrazadani, H., 2013, Analyzing and modelling Iran's electricity market price by time series approach, international conference "Modernization of economics and social spheres in Russia and CIS countries: Quantitative research methods", December 4-6, 2013, Moscow. The author of the essay in this study was awarded first prize winner at the conference (December, 2013).

Submitted paper

Nasrazadani, H., Muñoz Gracia,P., 2016. The Electricity Journal, Elsevier.

Appendix (A): Rational distributed lag model for Spanish market time series (price and loads).

Table A.1: SAS code and its complementary results for our best "Rational distributed lag model" for Spanish electricity market time series.

```
****the best model for spain-transfer function(arimax)*****;
proc arima;
 identify var=price(1,7) nlag=24;
 estimate q=(1 2 3 4 )(7);
 identify var=load(1,7) nlag=24;
 estimate p=(7) q=(1 2 3 4 9)(7);
 identify var=price(1,7) crosscorr=(load(1,7) WIND) nlag=24 ;
 estimate input=((1)/(1)load (7)WIND)P=4 Q=(7)ML MAXIT=100 NOCONSTANT;
 run;
quit;
In other words, you will have something like:
0*load(t=0) + a*load(t=1)

******##########################################################
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               Obs           data           price           load           wind

                 1       20070702          37.156        58.6573        80.1917
                 2       20070703          36.383        60.7011        63.4517
                 3       20070704          36.728        60.2869        78.3615
                 4       20070705          38.821        64.5921         58.433
                 5       20070706          39.747        64.7238        42.1532
                 6       20070707          37.439        60.8149        40.8772
                 7       20070708          33.805        56.3132        59.1048
                 8       20070709          35.814        64.4359        95.1808
                 9       20070710          38.195        65.1375        79.5145
                10       20070711          38.053        64.3218        59.5999
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                                   The ARIMA Procedure
                                 Name of Variable = price

                      Period(s) of Differencing                         1,7
                      Mean of Working Series                       0.000261
                      Standard Deviation                           4.662842
                      Number of Observations                           1179
                      Observation(s) eliminated by differencing          8
                                     Autocorrelations

  Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1      Std Error

    0     21.742097        1.00000    |                    |********************|              0
    1     -4.484306        -.20625    |                ****|.                   |       0.029123
    2     -3.196784        -.14703    |                 ***|.                   |       0.030337
    3     -2.309611        -.10623    |                  **|.                   |       0.030936
    4      1.008662        0.04639    |                   .|*                   |       0.031243
    5      2.406029        0.11066    |                   .|**                  |       0.031302
    6      3.069176        0.14116    |                   .|***                 |       0.031632
    7    -10.639519        -.48935    |          **********|.                   |       0.032162
    8      1.593905        0.07331    |                 . |*.                   |       0.037955
    9      1.268290        0.05833    |                 . |*.                   |       0.038075
   10      0.588830        0.02708    |                 . |*.                   |       0.038151
   11      0.951674        0.04377    |                 . |*.                   |       0.038167
   12     -0.913874        -.04203    |                 .*| .                   |       0.038210
   13     -0.671683        -.03089    |                 .*| .                   |       0.038249
   14     -0.623600        -.02868    |                 .*| .                   |       0.038270
   15      1.076981        0.04953    |                 . |*.                   |       0.038288
   16     -0.254249        -.01169    |                 . | .                   |       0.038343
   17      0.995121        0.04577    |                 . |*.                   |       0.038346
   18     -1.543744        -.07100    |                 .*| .                   |       0.038392
   19      0.875727        0.04028    |                 . |*.                   |       0.038503
   20     -0.584252        -.02687    |                 .*| .                   |       0.038539
   21      0.921286        0.04237    |                 . |*.                   |       0.038555
   22     -1.048968        -.04825    |                 .*| .                   |       0.038594
   23      0.175963        0.00809    |                 . | .                   |       0.038645
   24     -0.893016        -.04107    |                 .*| .                   |       0.038647

                                  "." marks two standard errors
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```

```
The ARIMA Procedure
                           Inverse Autocorrelations
    Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

      1        0.42684    |                   .|*********           |
      2        0.37741    |                   .|********            |
      3        0.33913    |                   .|*******             |
      4        0.29306    |                   .|******              |
      5        0.28086    |                   .|******              |
      6        0.31514    |                   .|******              |
      7        0.67837    |                   .|**************      |
      8        0.29059    |                   .|******              |
      9        0.26964    |                   .|*****               |
     10        0.23498    |                   .|*****               |
     11        0.18175    |                   .|****                |
     12        0.17462    |                   .|***                 |
     13        0.20730    |                   .|****                |
     14        0.38956    |                   .|********            |
     15        0.16481    |                   .|***                 |
     16        0.15562    |                   .|***                 |
     17        0.11887    |                   .|**                  |
     18        0.07722    |                   .|**                  |
     19        0.06792    |                   .|*                   |
     20        0.09282    |                   .|**                  |
     21        0.14907    |                   .|***                 |
     22        0.07169    |                   .|*                   |
     23        0.05980    |                   .|*                   |
     24        0.03811    |                   .|*                   |

                           Sectionial Autocorrelations
    Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
      1       -0.20625    |                ****|.                   |
      2       -0.19799    |                ****|.                   |
      3       -0.19936    |                ****|.                   |
      4       -0.06964    |                   *|.                   |
      5        0.05676    |                   .|*                   |
      6        0.19165    |                   .|****                |
      7       -0.42148    |            ********|.                   |
      8       -0.09341    |                  **|.                   |
      9       -0.08929    |                  **|.                   |
     10       -0.13562    |                 ***|.                   |
     11        0.00631    |                   .|.                   |
     12        0.02243    |                   .|.                   |
     13        0.10288    |                   .|**                  |
     14       -0.31427    |              ******|.                   |
     15       -0.03151    |                   *|.                   |
     16       -0.08426    |                  **|.                   |
     17       -0.04905    |                   *|.                   |
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                             The ARIMA Procedure
                           Sectionial Autocorrelations
    Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

     18       -0.04051    |                   *|.                   |
     19        0.05189    |                   .|*                   |
     20        0.03074    |                   .|*                   |
     21       -0.21577    |                ****|.                   |
     22       -0.06417    |                   *|.                   |
     23       -0.09177    |                  **|.                   |
     24       -0.09300    |                  **|.                   |
```

Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	129.95	6	<.0001	-0.206	-0.147	-0.106	0.046	0.111	0.141
12	430.15	12	<.0001	-0.489	0.073	0.058	0.027	0.044	-0.042
18	443.93	18	<.0001	-0.031	-0.029	0.050	-0.012	0.046	-0.071
24	453.81	24	<.0001	0.040	-0.027	0.042	-0.048	0.008	-0.041

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0008601	0.0016312	0.53	0.5981	0
MA1,1	0.29158	0.02919	9.99	<.0001	1
MA1,2	0.19987	0.03028	6.60	<.0001	2
MA1,3	0.10162	0.03027	3.36	0.0008	3
MA1,4	-0.02782	0.02921	-0.95	0.3411	4
MA2,1	0.96458	0.0077036	125.21	<.0001	7

```
Constant Estimate       0.00086
Variance Estimate      9.978138
Std Error Estimate     3.158819
```

```
                              AIC                    6064.009
                              SBC                    6094.444
                              Number of Residuals        1179
                       * AIC and SBC do not include log determinant.
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                                          The ARIMA Procedure
                            Correlations of Parameter Estimates

              Parameter        MU     MA1,1     MA1,2     MA1,3     MA1,4     MA2,1

              MU            1.000    -0.001     0.000     0.000     0.000     0.038
              MA1,1        -0.001     1.000    -0.280    -0.188    -0.093    -0.014
              MA1,2         0.000    -0.280     1.000    -0.233    -0.189    -0.005
              MA1,3         0.000    -0.188    -0.233     1.000    -0.279    -0.016
              MA1,4         0.000    -0.093    -0.189    -0.279     1.000     0.001
              MA2,1         0.038    -0.014    -0.005    -0.016     0.001     1.00

                             Autocorrelation Check of Residuals

   To       Chi-           Pr >
  Lag     Square     DF    ChiSq    --------------------Autocorrelations--------------------

    6       2.36      1   0.1244     0.001    -0.002    -0.006    -0.006     0.024     0.036
   12       8.70      7   0.2746    -0.001    -0.001    -0.044    -0.034     0.003    -0.047
   18      16.76     13   0.2103    -0.043    -0.035     0.014    -0.043     0.009    -0.039
   24      19.08     19   0.4518    -0.006    -0.034     0.003    -0.017    -0.014    -0.016
   30      29.30     25   0.2516     0.044    -0.011     0.046     0.007     0.052     0.039
   36      47.16     31   0.0316     0.039     0.063     0.053    -0.028     0.045     0.059
   42      53.78     37   0.0367     0.049    -0.029     0.016     0.016    -0.018     0.037
   48      62.91     43   0.0254    -0.019    -0.010    -0.055     0.055     0.012    -0.028

                                   Model for variable price

                             Estimated Mean              0.00086
                             Period(s) of Differencing       1,7

                                     Moving Average Factors

         Factor 1:  1 - 0.29158 B**(1) - 0.19987 B**(2) - 0.10162 B**(3) + 0.02782 B**(4)
         Factor 2:  1 - 0.96458 B**(7)

                                    Name of Variable = load

                     Period(s) of Differencing                     1,7
                     Mean of Working Series                   -0.00595
                     Standard Deviation                       3.085478
                     Number of Observations                       1179
                     Observation(s) eliminated by differencing       8
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                                     The ARIMA Procedure
                                       Autocorrelations

  Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1      Std Error

    0      9.520177        1.00000    |                    |********************|              0
    1     -1.620435        -.17021    |                 ***|.                   |       0.029123
    2     -1.178880        -.12383    |                  **|.                   |       0.029955
    3     -0.797682        -.08379    |                  **|.                   |       0.030386
    4      1.102170        0.11577    |                   .|**                  |       0.030582
    5      0.100393        0.01055    |                   .|.                   |       0.030951
    6      0.602282        0.06326    |                   .|*                   |       0.030954
    7     -4.197721        -.44093    |           *********|.                   |       0.031064
    8      1.393425        0.14637    |                   .|***                 |       0.035983
    9      0.117475        0.01234    |                   .|.                   |       0.036484
   10     -0.345217        -.03626    |                   *|.                   |       0.036488
   11     -0.815508        -.08566    |                  **|.                   |       0.036518
   12      1.050343        0.11033    |                   .|**                  |       0.036688
   13      0.379767        0.03989    |                   .|*                   |       0.036969
   14     -0.758874        -.07971    |                  **|.                   |       0.037005
   15     -0.589298        -.06190    |                   *|.                   |       0.037151
   16      0.281424        0.02956    |                   .|*                   |       0.037238
   17      0.745886        0.07835    |                   .|**                  |       0.037258
   18      0.289684        0.03043    |                   .|*                   |       0.037397
   19     -0.690228        -.07250    |                   *|.                   |       0.037418
   20     -0.404875        -.04253    |                  .*| .                  |       0.037537
   21      0.532292        0.05591    |                  . |*.                  |       0.037578
   22     -0.337466        -.03545    |                  .*| .                  |       0.037649
   23      0.136987        0.01439    |                  . | .                  |       0.037677
   24     -0.375737        -.03947    |                  .*| .                  |       0.037682

                                 "." marks two standard errors
                                    Inverse Autocorrelations

              Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

                1        0.32432    |                   .|******              |
```

```
               2        0.36515    |                   .|*******             |
               3        0.27823    |                   .|******              |
               4        0.23870    |                   .|*****               |
               5        0.28468    |                   .|******              |
               6        0.23063    |                   .|*****               |
               7        0.65250    |                   .|*************       |
               8        0.22783    |                   .|*****               |
               9        0.27353    |                   .|*****               |
              10        0.20893    |                   .|****                |
              11        0.16957    |                   .|***                 |
              12        0.16380    |                   .|***                 |
              13        0.14667    |                   .|***                 |
              14        0.37753    |                   .|********            |
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```

The ARIMA Procedure
Inverse Autocorrelations

```
              Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

              15        0.15174    |                   .|***                 |
              16        0.14708    |                   .|***                 |
              17        0.10082    |                   .|**                  |
              18        0.06023    |                   .|*                   |
              19        0.07227    |                   .|*                   |
              20        0.07190    |                   .|*                   |
              21        0.14573    |                   .|***                 |
              22        0.07330    |                   .|*                   |
              23        0.04816    |                   .|*                   |
              24        0.03890    |                   .|*                   |

                              Sectional Autocorrelations

              Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

               1       -0.17021    |                 ***|.                   |
               2       -0.15736    |                 ***|.                   |
               3       -0.14252    |                 ***|.                   |
               4        0.05407    |                   .|*                   |
               5        0.01447    |                   .|.                   |
               6        0.09125    |                   .|**                  |
               7       -0.42109    |            ********|.                   |
               8        0.00341    |                   .|.                   |
               9       -0.10092    |                  **|.                   |
              10       -0.12999    |                 ***|.                   |
              11       -0.06388    |                   *|.                   |
              12        0.05558    |                   .|*                   |
              13        0.10105    |                   .|**                  |
              14       -0.30403    |              ******|.                   |
              15       -0.02596    |                   *|.                   |
              16       -0.10227    |                  **|.                   |
              17       -0.03384    |                   *|.                   |
              18       -0.01375    |                   .|.                   |
              19        0.01240    |                   .|.                   |
              20        0.01489    |                   .|.                   |
              21       -0.20841    |                ****|.                   |
              22       -0.08605    |                  **|.                   |
              23       -0.06828    |                   *|.                   |
              24       -0.08234    |                  **|.                   |

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                                The ARIMA Procedure

                       Autocorrelation Check for White Noise

 To        Chi-             Pr >
 Lag      Square     DF     ChiSq    --------------------Autocorrelations--------------------

   6       81.46      6    <.0001    -0.170    -0.124    -0.084     0.116     0.011     0.063
  12      362.93     12    <.0001    -0.441     0.146     0.012    -0.036    -0.086     0.110
  18      386.52     18    <.0001     0.040    -0.080    -0.062     0.030     0.078     0.030
  24      402.40     24    <.0001    -0.073    -0.043     0.056    -0.035     0.014    -0.039

                       Conditional Least Squares Estimation

                                    Standard                 Approx
            Parameter      Estimate        Error    t Value    Pr > |t|     Lag

            MU           -0.0027045    0.0035284      -0.77      0.4435       0
            MA1,1           0.18668      0.02913       6.41      <.0001       1
            MA1,2           0.20748      0.02968       6.99      <.0001       2
            MA1,3           0.06867      0.02966       2.32      0.0208       3
            MA1,4          -0.06599      0.02952      -2.24      0.0256       4
            MA1,5           0.08078      0.02764       2.92      0.0035       9
            MA2,1           0.91362      0.01335      68.43      <.0001       7
            AR1,1           0.09310      0.03287       2.83      0.0047       7
```

```
Constant Estimate      -0.00245
Variance Estimate      5.316833
Std Error Estimate     2.305826
AIC                    5323.795
SBC                    5364.374
Number of Residuals        1179
* AIC and SBC do not include log determinant.
```

Correlations of Parameter Estimates

Parameter	MU	MA1,1	MA1,2	MA1,3	MA1,4	MA1,5	MA2,1	AR1,1
MU	1.000	-0.002	0.002	0.001	-0.001	-0.004	-0.072	-0.030
MA1,1	-0.002	1.000	-0.188	-0.189	-0.055	-0.053	0.003	0.008
MA1,2	0.002	-0.188	1.000	-0.159	-0.195	-0.010	-0.020	-0.039
MA1,3	0.001	-0.189	-0.159	1.000	-0.187	-0.025	-0.026	-0.018
MA1,4	-0.001	-0.055	-0.195	-0.187	1.000	0.004	-0.017	0.128
MA1,5	-0.004	-0.053	-0.010	-0.025	0.004	1.000	-0.030	-0.013
MA2,1	-0.072	0.003	-0.020	-0.026	-0.017	-0.030	1.000	0.437
AR1,1	-0.030	0.008	-0.039	-0.018	0.128	-0.013	0.437	1.000

The ARIMA Procedure
Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	.	0	.	0.000	0.005	0.001	0.000	-0.042	0.019
12	9.56	5	0.0888	-0.001	0.044	0.002	-0.035	-0.027	0.045
18	14.95	11	0.1847	0.023	0.003	-0.026	-0.000	0.037	0.044
24	21.07	17	0.2231	-0.038	-0.015	0.048	-0.029	0.017	-0.002
30	31.36	23	0.1142	0.069	0.016	0.028	0.021	0.048	-0.001
36	42.38	29	0.0519	0.009	-0.069	0.026	0.016	0.011	-0.055
42	51.81	35	0.0334	0.019	-0.050	0.027	-0.061	0.021	0.001
48	55.07	41	0.0699	0.043	-0.006	0.020	-0.000	-0.019	0.001

```
           Model for variable Spanish load
        Estimated Mean                -0.0027
        Period(s) of Differencing         1,7
               Autoregressive Factors
             Factor 1:  1 - 0.0931 B**(7)
               Moving Average Factors

Factor 1:  1 - 0.18668 B**(1) - 0.20748 B**(2) - 0.06867
        B**(3) + 0.06599 B**(4) - 0.08078 B**(9)
             Factor 2:  1 - 0.91362 B**(7)


              Name of Variable = price

Period(s) of Differencing                        1,7
Mean of Working Series                      0.000261
Standard Deviation                          4.662842
Number of Observations                          1179
Observation(s) eliminated by differencing          8
```


The ARIMA Procedure
Autocorrelations

```
Lag   Covariance   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1    Std Error

  0    21.742097      1.00000    |                    |********************|           0
  1    -4.484306      -.20625    |                ****|.                   |    0.029123
  2    -3.196784      -.14703    |                 ***|.                   |    0.030337
  3    -2.309611      -.10623    |                  **|.                   |    0.030936
  4     1.008662      0.04639    |                   .|*                   |    0.031243
  5     2.406029      0.11066    |                   .|**                  |    0.031302
  6     3.069176      0.14116    |                   .|***                 |    0.031632
  7   -10.639519      -.48935    |          **********|.                   |    0.032162
  8     1.593905      0.07331    |                  . |*.                  |    0.037955
  9     1.268290      0.05833    |                  . |*.                  |    0.038075
 10     0.588830      0.02708    |                  . |*.                  |    0.038151
 11     0.951674      0.04377    |                  . |*.                  |    0.038167
 12    -0.913874      -.04203    |                  .*| .                  |    0.038210
 13    -0.671683      -.03089    |                  .*| .                  |    0.038249
 14    -0.623600      -.02868    |                  .*| .                  |    0.038270
 15     1.076981      0.04953    |                  . |*.                  |    0.038288
 16    -0.254249      -.01169    |                  . | .                  |    0.038343
 17     0.995121      0.04577    |                  . |*.                  |    0.038346
 18    -1.543744      -.07100    |                  .*| .                  |    0.038392
 19     0.875727      0.04028    |                  . |*.                  |    0.038503
 20    -0.584252      -.02687    |                  .*| .                  |    0.038539
 21     0.921286      0.04237    |                  . |*.                  |    0.038555
```

```
   22     -1.048968        -.04825    |                 .*| .                |       0.038594
   23      0.175963        0.00809    |                 . | .                |       0.038645
   24     -0.893016        -.04107    |                 .*| .                |       0.038647

                                 "." marks two standard errors

 Inverse Autocorrelations

              Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

                1        0.42684    |                    .|*********           |
                2        0.37741    |                    .|********            |
                3        0.33913    |                    .|*******             |
                4        0.29306    |                    .|******              |
                5        0.28086    |                    .|******              |
                6        0.31514    |                    .|******              |
                7        0.67837    |                    .|**************      |
                8        0.29059    |                    .|******              |
                9        0.26964    |                    .|*****               |
               10        0.23498    |                    .|*****               |
               11        0.18175    |                    .|****                |
               12        0.17462    |                    .|***                 |
               13        0.20730    |                    .|****                |
               14        0.38956    |                    .|********            |


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                                       The ARIMA Procedure
                                     Inverse Autocorrelations
              Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

               15        0.16481    |                    .|***                 |
               16        0.15562    |                    .|***                 |
               17        0.11887    |                    .|**                  |
               18        0.07722    |                    .|**                  |
               19        0.06792    |                    .|*                   |
               20        0.09282    |                    .|**                  |
               21        0.14907    |                    .|***                 |
               22        0.07169    |                    .|*                   |
               23        0.05980    |                    .|*                   |
               24        0.03811    |                    .|*                   |

                                     Sectionial Autocorrelations
              Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

                1       -0.20625    |                 ****|.                   |
                2       -0.19799    |                 ****|.                   |
                3       -0.19936    |                 ****|.                   |
                4       -0.06964    |                    *|.                   |
                5        0.05676    |                    .|*                   |
                6        0.19165    |                    .|****                |
                7       -0.42148    |             ********|.                   |
                8       -0.09341    |                   **|.                   |
                9       -0.08929    |                   **|.                   |
               10       -0.13562    |                  ***|.                   |
               11        0.00631    |                    .|.                   |
               12        0.02243    |                    .|.                   |
               13        0.10288    |                    .|**                  |
               14       -0.31427    |               ******|.                   |
               15       -0.03151    |                    *|.                   |
               16       -0.08426    |                   **|.                   |
               17       -0.04905    |                    *|.                   |
               18       -0.04051    |                    *|.                   |
               19        0.05189    |                    .|*                   |
               20        0.03074    |                    .|*                   |
               21       -0.21577    |                 ****|.                   |
               22       -0.06417    |                    *|.                   |
               23       -0.09177    |                   **|.                   |
               24       -0.09300    |                   **|.                   |

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                                       The ARIMA Procedure
                              Autocorrelation Check for White Noise
   To        Chi-             Pr >
  Lag      Square     DF     ChiSq    --------------------Autocorrelations--------------------

    6      129.95      6    <.0001    -0.206    -0.147    -0.106     0.046     0.111     0.141
   12      430.15     12    <.0001    -0.489     0.073     0.058     0.027     0.044    -0.042
   18      443.93     18    <.0001    -0.031    -0.029     0.050    -0.012     0.046    -0.071
   24      453.81     24    <.0001     0.040    -0.027     0.042    -0.048     0.008    -0.041
```

```
                              Variable load has been differenced.
                    Period(s) of Differencing                         1,7
                    Number of Observations                           1179
                    Observation(s) eliminated by differencing           8
                    Variance of transformed series price         10.41687
                    Variance of transformed series load          5.284384
                          Both series have been prewhitened.
                                   Crosscorrelations
        Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

        -24      0.378540       0.05102    |                   .|*                  |
        -23      0.161750       0.02180    |                   .|.                  |
        -22    -0.0028622       -.00039    |                   .|.                  |
        -21     -0.023775       -.00320    |                   .|.                  |
        -20      0.165742       0.02234    |                   .|.                  |
        -19      0.012529       0.00169    |                   .|.                  |
        -18      0.182354       0.02458    |                   .|.                  |
        -17     -0.255006       -.03437    |                   *|.                  |
        -16     -0.039676       -.00535    |                   .|.                  |
        -15      0.096402       0.01299    |                   .|.                  |
        -14      0.253456       0.03416    |                   .|*                  |
        -13     -0.455708       -.06142    |                   *|.                  |
        -12      0.051211       0.00690    |                   .|.                  |
        -11     -0.135061       -.01820    |                   .|.                  |
        -10     -0.431910       -.05821    |                   *|.                  |
         -9      0.023287       0.00314    |                   .|.                  |
         -8     -0.271501       -.03659    |                   *|.                  |
         -7      0.217192       0.02927    |                   .|*                  |
         -6      0.437010       0.05890    |                   .|*                  |
         -5      0.257512       0.03471    |                   .|*                  |
         -4     -0.328242       -.04424    |                   *|.                  |
         -3      0.487735       0.06574    |                   .|*                  |
         -2     -0.103310       -.01392    |                   .|.                  |
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                                  The ARIMA Procedure
                                   Crosscorrelations
        Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

         -1     -0.094022       -.01267    |                   .|.                  |
          0      0.121162       0.01633    |                   .|.                  |
          1      0.400103       0.05393    |                   .|*                  |
          2     -0.161487       -.02177    |                   .|.                  |
          3      0.306811       0.04135    |                   .|*                  |
          4     -0.588615       -.07934    |                  **|.                  |
          5     -0.024339       -.00328    |                   .|.                  |
          6      0.369814       0.04984    |                   .|*                  |
          7      0.292240       0.03939    |                   .|*                  |
          8      0.108060       0.01456    |                   .|.                  |
          9     -0.010488       -.00141    |                   .|.                  |
         10     -0.387848       -.05228    |                   *|.                  |
         11      0.036369       0.00490    |                   .|.                  |
         12      0.027539       0.00371    |                   .|.                  |
         13     -0.119397       -.01609    |                   .|.                  |
         14     -0.243621       -.03284    |                   *|.                  |
         15     -0.099855       -.01346    |                   .|.                  |
         16     -0.242307       -.03266    |                   *|.                  |
         17     -0.055860       -.00753    |                   .|.                  |
         18      0.163411       0.02202    |                   .|.                  |
         19     -0.059445       -.00801    |                   .|.                  |
         20     0.0094008       0.00127    |                   .|.                  |
         21     -0.113381       -.01528    |                   .|.                  |
         22      0.029807       0.00402    |                   .|.                  |
         23     0.0010872       0.00015    |                   .|.                  |
         24      0.616133       0.08304    |                   .|**                 |

                              "." marks two standard errors
                          Crosscorrelation Check Between Series
  To       Chi-             Pr >
 Lag      Square     DF     ChiSq    --------------------Crosscorrelations-------------------

   5       13.75      6    0.0325     0.016     0.054    -0.022     0.041    -0.079    -0.003
  11       22.01     12    0.0374     0.050     0.039     0.015    -0.001    -0.052     0.005
  17       25.14     18    0.1210     0.004    -0.016    -0.033    -0.013    -0.033    -0.008
  23       26.09     24    0.3488     0.022    -0.008     0.001    -0.015     0.004     0.000

                      Both variables have been prewhitened by the following filter:
                                   Prewhitening Filter
                         The SAS System        12:40 Thursday, April 19, 2012  48
                                   The ARIMA Procedure
                                  Autoregressive Factors
                               Factor 1:  1 - 0.0931 B**(7)
                                  Moving Average Factors

                         Factor 1:  1 - 0.18668 B**(1) - 0.20748 B**(2) - 0.06867
                                 B**(3) + 0.06599 B**(4) - 0.08078 B**(9)
                                     Factor 2:  1 - 0.91362 B**(7)
```

```
                           Correlation of price and wind
                         Variance of input =       2382.982
                         Number of Observations        1179
                                  Crosscorrelations

        Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

        -24      8.054579       0.03532    |                    .|*                  |
        -23      6.236102       0.02734    |                    .|*                  |
        -22      2.574756       0.01129    |                    .|.                  |
        -21      0.795841       0.00349    |                    .|.                  |
        -20      2.474450       0.01085    |                    .|.                  |
        -19     -3.981266       -.01746    |                    .|.                  |
        -18     -3.196014       -.01401    |                    .|.                  |
        -17     -8.918318       -.03911    |                    *|.                  |
        -16     -2.109574       -.00925    |                    .|.                  |
        -15     -3.974235       -.01743    |                    .|.                  |
        -14     -3.186908       -.01397    |                    .|.                  |
        -13     -5.536846       -.02428    |                    .|.                  |
        -12     -0.439727       -.00193    |                    .|.                  |
        -11     -1.437998       -.00631    |                    .|.                  |
        -10      6.318392       0.02771    |                    .|*                  |
         -9      3.931425       0.01724    |                    .|.                  |
         -8      0.401733       0.00176    |                    .|.                  |
         -7     -1.131262       -.00496    |                    .|.                  |
         -6     -2.700977       -.01184    |                    .|.                  |
         -5     -0.158212       -.00069    |                    .|.                  |
         -4     -0.395123       -.00173    |                    .|.                  |
         -3     -4.281998       -.01878    |                    .|.                  |
         -2    -17.444159       -.07649    |                   **|.                  |
         -1    -33.404607       -.14648    |                  ***|.                  |
          0    -40.264404       -.17656    |                 ****|.                  |
          1     36.699517       0.16092    |                    .|***                |
          2     35.403522       0.15524    |                    .|***                |
          3     14.569728       0.06389    |                    .|*                  |
          4     -4.737087       -.02077    |                    .|.                  |
```

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```
                                     The ARIMA Procedure
                                  Crosscorrelations

        Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

          5      7.848050       0.03441    |                    .|*                  |
          6     39.027825       0.17113    |                    .|***                |
          7     51.257816       0.22476    |                    .|****               |
          8    -26.595191       -.11662    |                   **|.                  |
          9    -35.170671       -.15422    |                  ***|.                  |
         10    -19.165087       -.08404    |                   **|.                  |
         11      2.841254       0.01246    |                    .|.                  |
         12     10.987767       0.04818    |                    .|*                  |
         13     -0.712319       -.00312    |                    .|.                  |
         14    -10.081771       -.04421    |                    *|.                  |
         15     -8.814879       -.03865    |                    *|.                  |
         16      2.278051       0.00999    |                    .|.                  |
         17      8.851342       0.03881    |                    .|*                  |
         18      7.152716       0.03136    |                    .|*                  |
         19     -1.753583       -.00769    |                    .|.                  |
         20      0.865907       0.00380    |                    .|.                  |
         21     -0.996565       -.00437    |                    .|.                  |
         22      6.382502       0.02799    |                    .|*                  |
         23      3.720054       0.01631    |                    .|.                  |
         24      5.158928       0.02262    |                    .|.                  |

                            "." marks two standard errors

                            Maximum Likelihood Estimation

                           Standard                 Approx
   Parameter      Estimate        Error    t Value    Pr > |t|     Lag    Variable    Shift

   MA1,1           0.97533    0.0080560     121.07      <.0001       7    price           0
   AR1,1          -0.28191      0.02895      -9.74      <.0001       1    price           0
   AR1,2          -0.24977      0.02953      -8.46      <.0001       2    price           0
   AR1,3          -0.19447      0.02953      -6.59      <.0001       3    price           0
   AR1,4          -0.08224      0.02904      -2.83      0.0046       4    price           0
   NUM1            0.04282      0.03847       1.11      0.2657       0    load            0
   NUM1,1         -0.11896      0.03942      -3.02      0.0026       1    load            0
   DEN1,1         -0.64999      0.19772      -3.29      0.0010       1    load            0
   NUM2           -0.01037    0.0012651      -8.20      <.0001       0    wind            0
   NUM1,1         -0.01040    0.0012684      -8.20      <.0001       7    wind            0

Variance Estimate      9.302393
                           Std Error Estimate     3.049982
                           AIC                    6001.676
                           SBC                    6052.391
```

```
                          Number of Residuals        1178
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                                The ARIMA Procedure
                        Correlations of Parameter Estimates

          Variable              price     price     price     price     price
          Parameter             MA1,1     AR1,1     AR1,2     AR1,3     AR1,4
          price      MA1,1      1.000    -0.032    -0.013     0.020    -0.019
          price      AR1,1     -0.032     1.000     0.263     0.226     0.174
          price      AR1,2     -0.013     0.263     1.000     0.277     0.226
          price      AR1,3      0.020     0.226     0.277     1.000     0.260
          price      AR1,4     -0.019     0.174     0.226     0.260     1.000
          load        NUM1     -0.052     0.009     0.016    -0.014     0.063
          load      NUM1,1      0.058    -0.000    -0.004     0.010    -0.011
          load      DEN1,1      0.013    -0.005    -0.005     0.001    -0.020
          wind        NUM2     -0.022     0.039     0.028     0.027     0.033
          wind      NUM1,1     -0.022     0.039     0.028     0.027     0.033
                        Correlations of Parameter Estimates
          Variable               load      load      load      wind      wind
          Parameter              NUM1    NUM1,1    DEN1,1      NUM2    NUM1,1
          price      MA1,1     -0.052     0.058     0.013    -0.022    -0.022
          price      AR1,1      0.009    -0.000    -0.005     0.039     0.039
          price      AR1,2      0.016    -0.004    -0.005     0.028     0.028
          price      AR1,3     -0.014     0.010     0.001     0.027     0.027
          price      AR1,4      0.063    -0.011    -0.020     0.033     0.033
          load        NUM1      1.000    -0.555    -0.074    -0.064    -0.064
          load      NUM1,1     -0.555     1.000    -0.224     0.076     0.076
          load      DEN1,1     -0.074    -0.224     1.000    -0.034    -0.034
          wind        NUM2     -0.064     0.076    -0.034     1.000     1.000
          wind      NUM1,1     -0.064     0.076    -0.034     1.000     1.000

            Autocorrelation Check of Residuals
   To        Chi-            Pr >
  Lag      Square     DF     ChiSq    --------------------Autocorrelations--------------------
    6        2.77      1    0.0959    -0.004    -0.009    -0.011    -0.010    -0.045     0.000
   12        6.84      7    0.4456     0.007     0.003    -0.027    -0.020     0.022    -0.042
   18       11.98     13    0.5295    -0.038    -0.026     0.017    -0.029     0.031    -0.011
   24       12.91     19    0.8433     0.005    -0.020     0.014     0.002    -0.006     0.010
   30       19.21     25    0.7868     0.048    -0.004     0.027     0.009     0.040     0.023
   36       33.34     31    0.3539     0.028     0.054     0.041    -0.041     0.047     0.049
   42       38.92     37    0.3833     0.029    -0.021     0.026     0.015    -0.037     0.032
   48       49.26     43    0.2371    -0.021    -0.015    -0.050     0.062     0.007    -0.037
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                                The ARIMA Procedure
                       Crosscorrelation Check of Residuals with Input load
   To        Chi-            Pr >
  Lag      Square     DF     ChiSq    --------------------Crosscorrelations-------------------

    5        4.49      3    0.2130     0.003     0.018     0.038     0.022    -0.039    -0.003
   11       13.15      9    0.1561     0.063     0.036     0.017     0.003    -0.042    -0.002
   17       15.29     15    0.4309     0.004    -0.010    -0.030    -0.013    -0.023    -0.008
   23       16.91     21    0.7164     0.030     0.009     0.014    -0.013     0.003     0.005
   29       44.26     27    0.0194     0.082    -0.010     0.050    -0.102    -0.014    -0.057
   35       52.37     33    0.0174     0.011    -0.022     0.014    -0.030     0.051    -0.051
   41       57.92     39    0.0260    -0.045     0.023     0.013    -0.009     0.028     0.034
   47       64.99     45    0.0271     0.028    -0.061     0.033    -0.017    -0.010     0.002

                                 Model for variable Spanish price
                                 Period(s) of Differencing    1,7
                                   No mean term in this model.
                                      Autoregressive Factors

           Factor 1:  1 + 0.28191 B**(1) + 0.24977 B**(2) + 0.19447 B**(3) + 0.08224 B**(4)
                                      Moving Average Factors

                                   Factor 1:  1 - 0.97533 B**(7)
                                          Input Number 1
                                 Input Variable              load
                                 Period(s) of Differencing     1,7
                                         Numerator Factors

                                Factor 1:  0.04282 + 0.11896 B**(1)
                                        Denominator Factors

                                   Factor 1:  1 + 0.64999 B**(1)

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                                        The ARIMA Procedure
                                          Input Number 2
                                      Input Variable    wind
                                         Numerator Factors
                                Factor 1:  -0.0104 + 0.0104 B**(7)
```

Appendix (B): Rational distributed lag model for Iranian electricity market time series (price and loads).

Table B.1: SAS code and its complementary results for one“Rational distributed lag model “ for Iranian electricity market time series.

```
****the model for Iran-transfer function(arimax)*****;
proc arima;
  identify var=price(1) crosscorr=(load(1,7)) nlag=24 ;
  estimate input=(/(1)load)P=4 Q=(7)ML MAXIT=100 NOCONSTANT;
  run;
quit;
                            The SAS System        14:03 Thursday, April 19, 2012 196

                                      The ARIMA Procedure

                                   Name of Variable = price

                      Period(s) of Differencing                       1
                      Mean of Working Series                    27.5371
                      Standard Deviation                       2286.155
                      Number of Observations                       1094
                      Observation(s) eliminated by differencing       1

                                        Autocorrelations

  Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1      Std Error

    0       5226503       1.00000    |                    |********************|           0
    1      -1543750       -.29537    |              ******|.                   |    0.030234
    2     15597.600       0.00298    |                   .|.                   |    0.032765
    3       -643049       -.12304    |                  **|.                   |    0.032766
    4     82715.775       0.01583    |                   .|.                   |    0.033185
    5        363535       0.06956    |                   .|*                   |    0.033192
    6       -522950       -.10006    |                  **|.                   |    0.033325
    7        469115       0.08976    |                   .|**                  |    0.033599
    8       -441866       -.08454    |                  **|.                   |    0.033817
    9     -8881.451       -.00170    |                   .|.                   |    0.034010
   10        519656       0.09943    |                   .|**                  |    0.034010
   11       -342431       -.06552    |                   *|.                   |    0.034274
   12     76956.158       0.01472    |                   .|.                   |    0.034389
   13       -311047       -.05951    |                   *|.                   |    0.034395
   14        368718       0.07055    |                   .|*                   |    0.034489
   15       -121964       -.02334    |                   .|.                   |    0.034620
   16     64665.376       0.01237    |                   .|.                   |    0.034635
   17    -29347.860       -.00562    |                   .|.                   |    0.034639
   18       -120908       -.02313    |                   .|.                   |    0.034639
   19        163071       0.03120    |                   .|*                   |    0.034654
   20       -470785       -.09008    |                  **|.                   |    0.034679
   21        375274       0.07180    |                   .|*                   |    0.034892
   22       -550155       -.10526    |                  **|.                   |    0.035027
   23        644193       0.12325    |                   .|**                  |    0.035315
   24        292082       0.05588    |                   .|*                   |    0.035706

                                   "." marks two standard errors
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                                      The ARIMA Procedure

                                   Inverse Autocorrelations

                Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

                  1        0.34588    |                   .|*******            |
                  2        0.19210    |                   .|****               |
                  3        0.20065    |                   .|****               |
                  4        0.04952    |                   .|*                  |
                  5        0.04237    |                   .|*                  |
                  6        0.08188    |                   .|**                 |
                  7       -0.00850    |                   .|.                  |
                  8        0.06167    |                   .|*                  |
                  9        0.02990    |                   .|*                  |
                 10       -0.06028    |                   *|.                  |
                 11        0.03968    |                   .|*                  |
                 12        0.01821    |                   .|.                  |
                 13        0.02240    |                   .|.                  |
                 14        0.01825    |                   .|.                  |
                 15       -0.01048    |                   .|.                  |
                 16        0.01178    |                   .|.                  |
                 17        0.03618    |                   .|*                  |
                 18        0.02053    |                   .|.                  |
                 19        0.04781    |                   .|*                  |
```

```
               20       0.05145    |                 .|*                 |
               21      -0.02447    |                 .|.                 |
               22       0.00797    |                 .|.                 |
               23      -0.10664    |                **|.                 |
               24      -0.09142    |                **|.                 |


                            Partial Autocorrelations

             Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

               1      -0.29537    |            ******|.                 |
               2      -0.09231    |                **|.                 |
               3      -0.16502    |               ***|.                 |
               4      -0.08412    |                **|.                 |
               5       0.03597    |                 .|*                 |
               6      -0.09815    |                **|.                 |
               7       0.03453    |                 .|*                 |
               8      -0.04972    |                 *|.                 |
               9      -0.06580    |                 *|.                 |
              10       0.09277    |                 .|**                |
              11      -0.02019    |                 .|.                 |
              12      -0.02236    |                 .|.                 |
              13      -0.02843    |                 *|.                 |
              14       0.02273    |                 .|.                 |
              15      -0.01032    |                 .|.                 |
              16       0.01976    |                 .|.                 |
              17      -0.00777    |                 .|.                 |

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                              The ARIMA Procedure

                            Partial Autocorrelations

             Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

              18      -0.01151    |                 .|.                 |
              19       0.01665    |                 .|.                 |
              20      -0.09494    |                **|.                 |
              21       0.01171    |                 .|.                 |
              22      -0.09586    |                **|.                 |
              23       0.05755    |                 .|*                 |
              24       0.11321    |                 .|**                |


                             Autocorrelation Check for White Noise

  To        Chi-             Pr >
 Lag      Square     DF     ChiSq    --------------------Autocorrelations--------------------

   6      128.99      6    <.0001    -0.295     0.003    -0.123     0.016     0.070    -0.100
  12      161.70     12    <.0001     0.090    -0.085    -0.002     0.099    -0.066     0.015
  18      172.56     18    <.0001    -0.060     0.071    -0.023     0.012    -0.006    -0.023
  24      221.36     24    <.0001     0.031    -0.090     0.072    -0.105     0.123     0.056
                         Variable load has been differenced.


                           Correlation of price and load

                    Period(s) of Differencing                     1,7
                    Variance of input =                       2.9708E8
                    Number of Observations                        1087
                    Observation(s) eliminated by differencing        8


                                Crosscorrelations

        Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

        -24        423699        0.01072    |                 .|.                 |
        -23       2728379        0.06903    |                 .|*                 |
        -22       2048333        0.05183    |                 .|*                 |
        -21      -1713343        -.04335    |                 *|.                 |
        -20       -347286        -.00879    |                 .|.                 |
        -19       -929027        -.02351    |                 .|.                 |
        -18        877302        0.02220    |                 .|.                 |
        -17        879160        0.02224    |                 .|.                 |
        -16      -1659754        -.04199    |                 *|.                 |
        -15       -871298        -.02205    |                 .|.                 |
        -14       1585153        0.04011    |                 .|*                 |
        -13        282951        0.00716    |                 .|.                 |
        -12        380886        0.00964    |                 .|.                 |


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                                       The ARIMA Procedure
                                        Crosscorrelations

        Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

        -11      -1493320        -.03778    |                   *|.                   |
        -10        780349        0.01974    |                   .|.                   |
         -9       -480431        -.01216    |                   .|.                   |
         -8       2696377        0.06822    |                   .|*                   |
         -7      -4014279        -.10157    |                  **|.                   |
         -6       -454445        -.01150    |                   .|.                   |
         -5      -1239290        -.03136    |                   *|.                   |
         -4        685159        0.01734    |                   .|.                   |
         -3     54876.723        0.00139    |                   .|.                   |
         -2    -85086.298        -.00215    |                   .|.                   |
         -1      -2492111        -.06305    |                   *|.                   |
          0       4722115        0.11948    |                   .|**                  |
          1        313438        0.00793    |                   .|.                   |
          2       2121247        0.05367    |                   .|*                   |
          3       1154121        0.02920    |                   .|*                   |
          4      -1792324        -.04535    |                   *|.                   |
          5       -146036        -.00369    |                   .|.                   |
          6       -646728        -.01636    |                   .|.                   |
          7     37035.613        0.00094    |                   .|.                   |
          8     -6436.369        -.00016    |                   .|.                   |
          9        267246        0.00676    |                   .|.                   |
         10      -2931792        -.07418    |                   *|.                   |
         11       1302950        0.03297    |                   .|*                   |
         12        141458        0.00358    |                   .|.                   |
         13       1988575        0.05031    |                   .|*                   |
         14      -1521365        -.03849    |                   *|.                   |
         15        119326        0.00302    |                   .|.                   |
         16      -2180693        -.05517    |                   *|.                   |
         17       2467410        0.06243    |                   .|*                   |
         18       -707317        -.01790    |                   .|.                   |
         19       1190478        0.03012    |                   .|*                   |
         20      -2995015        -.07578    |                  **|.                   |
         21       3078101        0.07788    |                   .|**                  |
         22       -333070        -.00843    |                   .|.                   |
         23        688703        0.01743    |                   .|.                   |
         24        309595        0.00783    |                   .|.                   |

                              "." marks two standard errors


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                                 The ARIMA Procedure

                              Maximum Likelihood Estimation

                             Standard                 Approx
    Parameter      Estimate     Error    t Value    Pr > |t|     Lag    Variable    Shift

    MA1,1          -0.07162   0.03100      -2.31      0.0209       7    price           0
    AR1,1          -0.35711   0.03048     -11.72      <.0001       1    price           0
    AR1,2          -0.17696   0.03165      -5.59      <.0001       2    price           0
    AR1,3          -0.21667   0.03169      -6.84      <.0001       3    price           0
    AR1,4          -0.08001   0.03073      -2.60      0.0092       4    price           0
    NUM1            0.01561 0.0030088       5.19      <.0001       0    load            0
    DEN1,1          0.59638   0.11087       5.38      <.0001       1    load            0


                             Variance Estimate       4473070
                             Std Error Estimate     2114.963
                             AIC                    19719.75
                             SBC                    19754.68
                             Number of Residuals        1086


                          Correlations of Parameter Estimates

     Variable              price      price      price      price      price       load       load
     Parameter             MA1,1      AR1,1      AR1,2      AR1,3      AR1,4       NUM1     DEN1,1

     price       MA1,1     1.000     -0.084      0.018      0.019     -0.137     -0.043      0.037
     price       AR1,1    -0.084      1.000      0.328      0.156      0.197      0.024     -0.010
     price       AR1,2     0.018      0.328      1.000      0.343      0.154      0.007      0.012
     price       AR1,3     0.019      0.156      0.343      1.000      0.326     -0.016      0.028
     price       AR1,4    -0.137      0.197      0.154      0.326      1.000     -0.021      0.019
     load         NUM1    -0.043      0.024      0.007     -0.016     -0.021      1.000     -0.459
     load       DEN1,1     0.037     -0.010      0.012      0.028      0.019     -0.459      1.000
```

```
                                              Autocorrelation Check of Residuals

  To       Chi-             Pr >
  Lag      Square     DF     ChiSq    --------------------Autocorrelations--------------------

   6        9.22       1    0.0024     0.003     0.002    -0.011    -0.004    -0.003    -0.091
  12       26.48       7    0.0004     0.003    -0.057     0.001     0.104    -0.039    -0.006
  18       31.61      13    0.0027    -0.023     0.047    -0.002    -0.000    -0.033    -0.028
  24       60.11      19    <.0001    -0.014    -0.068     0.032    -0.069     0.105     0.063
  30       69.67      25    <.0001    -0.055    -0.013    -0.027     0.013    -0.067    -0.005
  36       93.65      31    <.0001     0.096    -0.060     0.020     0.071    -0.003    -0.056
  42      101.55      37    <.0001     0.020    -0.029    -0.036    -0.017     0.018     0.062
  48      117.81      43    <.0001    -0.031    -0.020    -0.021     0.023     0.065    -0.088


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                                The ARIMA Procedure
                             Model for variable price
                          Period(s) of Differencing    1
                            No mean term in this model.
                               Autoregressive Factors
         Factor 1:  1 + 0.35711 B**(1) + 0.17696 B**(2) + 0.21667 B**(3) + 0.08001 B**(4)
                              Moving Average Factors
                           Factor 1:  1 + 0.07162 B**(7)
                                  Input Number 1
                        Input Variable                  load
                        Period(s) of Differencing        1,7
                        Overall Regression Factor    0.015608
                                Denominator Factors
                           Factor 1:  1 - 0.59638 B**(1)

mreg3_load=arima(Iran_load,order=c(3,1,3),seasonal=list(order=c(0,1,1), period=7),xreg=Iranday_load)
                                             mreg3_load

proc arima;
  identify var=load(1,7) nlag=24;
  estimate p=(3) q=(3)(7);
  identify var=price(1) crosscorr=(load(1,7)) nlag=24 ;
  estimate input=(/(1)load)P=4 Q=(7)ML MAXIT=100 NOCONSTANT;
  run;
 quit;

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                                The ARIMA Procedure
                             Name of Variable = load
                      Period(s) of Differencing                       1,7
                      Mean of Working Series                     -103.033
                      Standard Deviation                         17235.89
                      Number of Observations                         1087
                      Observation(s) eliminated by differencing         8


                                  Autocorrelations

  Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1      Std Error

    0     297075882        1.00000    |                    |********************|           0
    1     -40315506        -.13571    |                 ***|.                   |    0.030331
    2     -24836626        -.08360    |                  **|.                   |    0.030884
    3     -28030828        -.09436    |                  **|.                   |    0.031092
    4       8237388        0.02773    |                   .|*                   |    0.031354
    5       -691266        -.00233    |                   .|.                   |    0.031377
    6      14491928        0.04878    |                   .|*                   |    0.031377
    7    -154705704        -.52076    |          **********|.                   |    0.031447
    8      33673387        0.11335    |                  . |**                  |    0.038573
    9      25719822        0.08658    |                  . |**                  |    0.038878
   10      20694808        0.06966    |                  . |*.                  |    0.039055
   11      -4603518        -.01550    |                  . | .                  |    0.039169
   12      11698250        0.03938    |                  . |*.                  |    0.039175
   13      -5954659        -.02004    |                  . | .                  |    0.039211
   14      13635993        0.04590    |                  . |*.                  |    0.039221
   15     -12191482        -.04104    |                  .*| .                  |    0.039270
   16      -6260353        -.02107    |                  . | .                  |    0.039309
   17        504373        0.00170    |                  . | .                  |    0.039320
   18       4990487        0.01680    |                  . | .                  |    0.039320
   19      -6627683        -.02231    |                  . | .                  |    0.039327
   20       8391532        0.02825    |                  . |*.                  |    0.039338
   21       1783062        0.00600    |                  . | .                  |    0.039357
   22      -8839910        -.02976    |                  .*| .                  |    0.039358
   23       3648616        0.01228    |                  . | .                  |    0.039378
   24       6511623        0.02192    |                  . | .                  |    0.039382

                          "." marks two standard errors
```

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                                       The ARIMA Procedure
                                     Inverse Autocorrelations

                Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

                  1        0.27875    |                  .|******               |
                  2        0.18008    |                  .|****                 |
                  3        0.19628    |                  .|****                 |
                  4        0.20188    |                  .|****                 |
                  5        0.16045    |                  .|***                  |
                  6        0.20453    |                  .|****                 |
                  7        0.64609    |                  .|*************        |
                  8        0.17230    |                  .|***                  |
                  9        0.06411    |                  .|*                    |
                 10        0.06006    |                  .|*                    |
                 11        0.10884    |                  .|**                   |
                 12        0.07197    |                  .|*                    |
                 13        0.09386    |                  .|**                   |
                 14        0.30923    |                  .|******               |
                 15        0.08617    |                  .|**                   |
                 16        0.00083    |                  .|.                    |
                 17       -0.01653    |                  .|.                    |
                 18        0.03409    |                  .|*                    |
                 19        0.02302    |                  .|.                    |
                 20        0.02209    |                  .|.                    |
                 21        0.09150    |                  .|**                   |
                 22        0.02769    |                  .|*                    |
                 23       -0.01847    |                  .|.                    |
                 24       -0.02839    |                  *|.                    |


                                     Partial Autocorrelations

                Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

                  1       -0.13571    |                ***|.                    |
                  2       -0.10393    |                 **|.                    |
                  3       -0.12460    |                 **|.                    |
                  4       -0.01547    |                  .|.                    |
                  5       -0.02327    |                  .|.                    |
                  6        0.03653    |                  .|*                    |
                  7       -0.53197    |        ***********|.                    |
                  8       -0.05541    |                  *|.                    |
                  9       -0.02203    |                  .|.                    |
                 10       -0.03506    |                  *|.                    |
                 11       -0.01814    |                  .|.                    |
                 12        0.02414    |                  .|.                    |
                 13        0.00917    |                  .|.                    |
                 14       -0.31122    |             ******|.                    |
                 15       -0.03865    |                  *|.                    |
                 16       -0.00583    |                  .|.                    |
                 17        0.00201    |                  .|.                    |
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                                       The ARIMA Procedure
                                     Partial Autocorrelations

                Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

                 18       -0.00876    |                  .|.                    |
                 19        0.01088    |                  .|.                    |
                 20        0.02645    |                  .|*                    |
                 21       -0.17987    |               ****|.                    |
                 22       -0.07964    |                 **|.                    |
                 23        0.01487    |                  .|.                    |
                 24        0.05705    |                  .|*                    |

                             Autocorrelation Check for White Noise

   To       Chi-             Pr >
  Lag      Square     DF     ChiSq    --------------------Autocorrelations--------------------

    6       40.87      6    <.0001    -0.136     -0.084     -0.094      0.028     -0.002      0.049
   12      367.75     12    <.0001    -0.521      0.113      0.087      0.070     -0.015      0.039
   18      373.18     18    <.0001    -0.020      0.046     -0.041     -0.021      0.002      0.017
   24      376.35     24    <.0001    -0.022      0.028      0.006     -0.030      0.012      0.022

                              Conditional Least Squares Estimation
                                          Standard                 Approx
              Parameter        Estimate        Error    t Value    Pr > |t|     Lag

              MU              -45.32558     99.83272      -0.45      0.6499       0
              MA1,1             0.30291      0.32811       0.92      0.3561       3
              MA2,1             0.73168      0.02107      34.73      <.0001       7
              AR1,1             0.22009      0.33567       0.66      0.5122       3
```

```
                             Constant Estimate        -35.35
                             Variance Estimate      1.8304E8
                             Std Error Estimate     13529.36
                             AIC                     23769.2
                             SBC                    23789.16
                             Number of Residuals        1087
                      * AIC and SBC do not include log determinant.


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                                   The ARIMA Procedure
                           Correlations of Parameter Estimates
                      Parameter         MU     MA1,1     MA2,1     AR1,1

                      MU             1.000     0.004     0.002     0.004
                      MA1,1          0.004     1.000     0.169     0.996
                      MA2,1          0.002     0.169     1.000     0.164
                      AR1,1          0.004     0.996     0.164     1.000


                                   Autocorrelation Check of Residuals

  To       Chi-           Pr >
 Lag     Square     DF    ChiSq    --------------------Autocorrelations--------------------

   6      46.29      3    <.0001    -0.169    -0.101     0.003    -0.033    -0.045    -0.026
  12      56.90      9    <.0001    -0.062     0.014     0.048     0.055    -0.010     0.017
  18      68.57     15    <.0001    -0.050     0.039    -0.046    -0.016     0.061     0.019
  24      75.77     21    <.0001    -0.022    -0.012     0.037    -0.036    -0.022     0.052
  30      84.88     27    <.0001     0.014    -0.002    -0.043     0.018     0.041    -0.064
  36      86.67     33    <.0001     0.008    -0.007     0.034    -0.015    -0.009     0.004
  42      89.40     39    <.0001     0.029     0.033     0.010     0.018    -0.002    -0.008
  48      95.17     45    <.0001    -0.057    -0.013     0.018     0.000     0.011     0.035


                                         Model for variable load
                                Estimated Mean               -45.3256
                                Period(s) of Differencing         1,7
                                        Autoregressive Factors
                                    Factor 1:  1 - 0.22009 B**(3)
                                        Moving Average Factors
                                    Factor 1:  1 - 0.30291 B**(3)
                                    Factor 2:  1 - 0.73168 B**(7)
                                       Name of Variable = price

                           Period(s) of Differencing                          1
                           Mean of Working Series                       27.5371
                           Standard Deviation                          2286.155
                           Number of Observations                          1094
                           Observation(s) eliminated by differencing          1
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                                   The ARIMA Procedure
                                     Autocorrelations

 Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1      Std Error

   0       5226503        1.00000    |                    |********************|              0
   1      -1543750        -.29537    |              ******|.                   |       0.030234
   2     15597.600        0.00298    |                   .|.                   |       0.032765
   3       -643049        -.12304    |                  **|.                   |       0.032766
   4     82715.775        0.01583    |                   .|.                   |       0.033185
   5        363535        0.06956    |                   .|*                   |       0.033192
   6       -522950        -.10006    |                  **|.                   |       0.033325
   7        469115        0.08976    |                   .|**                  |       0.033599
   8       -441866        -.08454    |                  **|.                   |       0.033817
   9     -8881.451        -.00170    |                   .|.                   |       0.034010
  10        519656        0.09943    |                   .|**                  |       0.034010
  11       -342431        -.06552    |                   *|.                   |       0.034274
  12     76956.158        0.01472    |                   .|.                   |       0.034389
  13       -311047        -.05951    |                   *|.                   |       0.034395
  14        368718        0.07055    |                   .|*                   |       0.034489
  15       -121964        -.02334    |                   .|.                   |       0.034620
  16     64665.376        0.01237    |                   .|.                   |       0.034635
  17    -29347.860        -.00562    |                   .|.                   |       0.034639
  18       -120908        -.02313    |                   .|.                   |       0.034639
  19        163071        0.03120    |                   .|*                   |       0.034654
  20       -470785        -.09008    |                  **|.                   |       0.034679
  21        375274        0.07180    |                   .|*                   |       0.034892
  22       -550155        -.10526    |                  **|.                   |       0.035027
  23        644193        0.12325    |                   .|**                  |       0.035315
  24        292082        0.05588    |                   .|*                   |       0.035706

                                "." marks two standard errors
```

```
  Inverse Autocorrelations

              Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

                1        0.34588    |                   .|*******            |
                2        0.19210    |                   .|****               |
                3        0.20065    |                   .|****               |
                4        0.04952    |                   .|*                  |
                5        0.04237    |                   .|*                  |
                6        0.08188    |                   .|**                 |
                7       -0.00850    |                   .|.                  |
                8        0.06167    |                   .|*                  |
                9        0.02990    |                   .|*                  |
               10       -0.06028    |                   *|.                  |
               11        0.03968    |                   .|*                  |
               12        0.01821    |                   .|.                  |
               13        0.02240    |                   .|.                  |
               14        0.01825    |                   .|.                  |
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                                The ARIMA Procedure
                              Inverse Autocorrelations

              Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

               15       -0.01048    |                   .|.                  |
               16        0.01178    |                   .|.                  |
               17        0.03618    |                   .|*                  |
               18        0.02053    |                   .|.                  |
               19        0.04781    |                   .|*                  |
               20        0.05145    |                   .|*                  |
               21       -0.02447    |                   .|.                  |
               22        0.00797    |                   .|.                  |
               23       -0.10664    |                  **|.                  |
               24       -0.09142    |                  **|.                  |


                                      Partial Autocorrelations

              Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

                1       -0.29537    |              ******|.                  |
                2       -0.09231    |                  **|.                  |
                3       -0.16502    |                 ***|.                  |
                4       -0.08412    |                  **|.                  |
                5        0.03597    |                   .|*                  |
                6       -0.09815    |                  **|.                  |
                7        0.03453    |                   .|*                  |
                8       -0.04972    |                   *|.                  |
                9       -0.06580    |                   *|.                  |
               10        0.09277    |                   .|**                 |
               11       -0.02019    |                   .|.                  |
               12       -0.02236    |                   .|.                  |
               13       -0.02843    |                   *|.                  |
               14        0.02273    |                   .|.                  |
               15       -0.01032    |                   .|.                  |
               16        0.01976    |                   .|.                  |
               17       -0.00777    |                   .|.                  |
               18       -0.01151    |                   .|.                  |
               19        0.01665    |                   .|.                  |
               20       -0.09494    |                  **|.                  |
               21        0.01171    |                   .|.                  |
               22       -0.09586    |                  **|.                  |
               23        0.05755    |                   .|*                  |
               24        0.11321    |                   .|**                 |
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                                The ARIMA Procedure
                        Autocorrelation Check for White Noise

  To        Chi-            Pr >
 Lag      Square     DF     ChiSq    --------------------Autocorrelations--------------------

   6      128.99      6    <.0001    -0.295     0.003    -0.123     0.016     0.070    -0.100
  12      161.70     12    <.0001     0.090    -0.085    -0.002     0.099    -0.066     0.015
  18      172.56     18    <.0001    -0.060     0.071    -0.023     0.012    -0.006    -0.023
  24      221.36     24    <.0001     0.031    -0.090     0.072    -0.105     0.123     0.056

                                Variable load has been differenced.
                                   Correlation of price and load
                        Period(s) of Differencing                        1,7
                        Number of Observations                          1087
                        Observation(s) eliminated by differencing          8
                        Variance of transformed series price        14760986
                        Variance of transformed series load         1.8239E8
                                 Both series have been prewhitened.
```

```
                                    Crosscorrelations

        Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

        -24       2064844        0.03979    |                   .|*                  |
        -23       -981070        -.01891    |                   .|.                  |
        -22       2619921        0.05049    |                   .|*                  |
        -21      -2787279        -.05372    |                   *|.                  |
        -20       2025750        0.03904    |                   .|*                  |
        -19      -1682364        -.03242    |                   *|.                  |
        -18     63640.058        0.00123    |                   .|.                  |
        -17       2648451        0.05104    |                   .|*                  |
        -16      -2632359        -.05073    |                   *|.                  |
        -15       1647968        0.03176    |                   .|*                  |
        -14       -810627        -.01562    |                   .|.                  |
        -13       1323005        0.02550    |                   .|*                  |
        -12       -906969        -.01748    |                   .|.                  |
        -11       -514328        -.00991    |                   .|.                  |
        -10       2063361        0.03977    |                   .|*                  |
         -9      -2456164        -.04734    |                   *|.                  |
         -8       1950339        0.03759    |                   .|*                  |
         -7      -1196552        -.02306    |                   .|.                  |
         -6        624496        0.01204    |                   .|.                  |
         -5       -779445        -.01502    |                   .|.                  |
         -4        341980        0.00659    |                   .|.                  |
         -3        965471        0.01861    |                   .|.                  |
         -2      -1782764        -.03436    |                   *|.                  |
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                                   The ARIMA Procedure

                                    Crosscorrelations

        Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

         -1       -940375        -.01812    |                   .|.                  |
          0       3769924        0.07266    |                   .|*                  |
          1        482182        0.00929    |                   .|.                  |
          2        813607        0.01568    |                   .|.                  |
          3       1023834        0.01973    |                   .|.                  |
          4       -487888        -.00940    |                   .|.                  |
          5      -1141948        -.02201    |                   .|.                  |
          6       -836518        -.01612    |                   .|.                  |
          7       2572476        0.04958    |                   .|*                  |
          8        218796        0.00422    |                   .|.                  |
          9       -240553        -.00464    |                   .|.                  |
         10       -323457        -.00623    |                   .|.                  |
         11        433865        0.00836    |                   .|.                  |
         12       -524217        -.01010    |                   .|.                  |
         13     -1274.534        -.00002    |                   .|.                  |
         14       2034521        0.03921    |                   .|*                  |
         15    -48165.147        -.00093    |                   .|.                  |
         16      -1761685        -.03395    |                   *|.                  |
         17       2266411        0.04368    |                   .|*                  |
         18       -208356        -.00402    |                   .|.                  |
         19       -227130        -.00438    |                   .|.                  |
         20      -1270476        -.02449    |                   .|.                  |
         21       3463905        0.06676    |                   .|*                  |
         22       -673102        -.01297    |                   .|.                  |
         23       -690279        -.01330    |                   .|.                  |
         24       2158335        0.04160    |                   .|*                  |

                              "." marks two standard errors


                          Crosscorrelation Check Between Series

   To        Chi-            Pr >
  Lag      Square     DF     ChiSq    --------------------Crosscorrelations-------------------

    5        7.15      6    0.3076     0.073     0.009     0.016     0.020    -0.009    -0.022
   11       10.26     12    0.5931    -0.016     0.050     0.004    -0.005    -0.006     0.008
   17       15.37     18    0.6364    -0.010    -0.000     0.039    -0.001    -0.034     0.044
   23       21.28     24    0.6222    -0.004    -0.004    -0.024     0.067    -0.013    -0.013

Both variables have been prewhitened by the following filter:
Prewhitening Filter
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The ARIMA Procedure
Autoregressive Factors
Factor 1:  1 - 0.22009 B**(3)
Moving Average Factors
Factor 1:  1 - 0.30291 B**(3)
Factor 2:  1 - 0.73168 B**(7)
Maximum Likelihood Estimation
```

```
                          Standard                      Approx
Parameter       Estimate     Error    t Value    Pr > |t|     Lag    Variable    Shift

MA1,1           -0.07162   0.03100      -2.31      0.0209       7    price           0
AR1,1           -0.35711   0.03048     -11.72      <.0001       1    price           0
AR1,2           -0.17696   0.03165      -5.59      <.0001       2    price           0
AR1,3           -0.21667   0.03169      -6.84      <.0001       3    price           0
AR1,4           -0.08001   0.03073      -2.60      0.0092       4    price           0
NUM1             0.01561 0.0030089       5.19      <.0001       0    load            0
DEN1,1           0.59638   0.11087       5.38      <.0001       1    load            0


                          Variance Estimate       4473070
                          Std Error Estimate     2114.963
                          AIC                    19719.75
                          SBC                    19754.68
                          Number of Residuals        1086


                        Correlations of Parameter Estimates

 Variable              price      price      price      price      price       load       load
 Parameter             MA1,1      AR1,1      AR1,2      AR1,3      AR1,4       NUM1     DEN1,1

 price       MA1,1     1.000     -0.084      0.018      0.019     -0.137     -0.043      0.037
 price       AR1,1    -0.084      1.000      0.328      0.156      0.197      0.024     -0.010
 price       AR1,2     0.018      0.328      1.000      0.343      0.154      0.007      0.012
 price       AR1,3     0.019      0.156      0.343      1.000      0.326     -0.016      0.028
 price       AR1,4    -0.137      0.197      0.154      0.326      1.000     -0.021      0.019
 load         NUM1    -0.043      0.024      0.007     -0.016     -0.021      1.000     -0.459
 load       DEN1,1     0.037     -0.010      0.012      0.028      0.019     -0.459      1.000


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                             The ARIMA Procedure
                        Autocorrelation Check of Residuals

 To        Chi-            Pr >
Lag      Square     DF     ChiSq    --------------------Autocorrelations--------------------

  6        9.22      1    0.0024     0.003     0.002    -0.011    -0.004    -0.003    -0.091
 12       26.48      7    0.0004     0.003    -0.057     0.001     0.104    -0.039    -0.006
 18       31.61     13    0.0027    -0.023     0.047    -0.002    -0.000    -0.033    -0.028
 24       60.11     19    <.0001    -0.014    -0.068     0.032    -0.069     0.105     0.063
 30       69.67     25    <.0001    -0.055    -0.013    -0.027     0.013    -0.067    -0.005
 36       93.65     31    <.0001     0.096    -0.060     0.020     0.071    -0.003    -0.056
 42      101.55     37    <.0001     0.020    -0.029    -0.036    -0.017     0.018     0.062
 48      117.81     43    <.0001    -0.031    -0.020    -0.021     0.023     0.065    -0.088


                Crosscorrelation Check of Residuals with Input load

 To        Chi-            Pr >
Lag      Square     DF     ChiSq    --------------------Crosscorrelations-------------------

  5        7.41      4    0.1157     0.062    -0.017     0.023     0.024    -0.038    -0.011
 11       14.08     10    0.1695    -0.015     0.050     0.043    -0.008    -0.034     0.019
 17       23.04     16    0.1127     0.005     0.017     0.001    -0.009    -0.048     0.074
 23       28.88     22    0.1482    -0.001     0.008    -0.043     0.054    -0.006     0.023
 29       38.14     28    0.0958     0.025     0.006    -0.040     0.060    -0.039    -0.035
 35       40.33     34    0.2105     0.003    -0.003    -0.011     0.016     0.030    -0.027
 41       43.24     40    0.3345    -0.034    -0.002     0.019     0.005     0.027    -0.019
 47       53.60     46    0.2058     0.038    -0.015    -0.070     0.007     0.044    -0.031


                                Model for variable price
                             Period(s) of Differencing    1
                              No mean term in this model.
                                Autoregressive Factors
           Factor 1:  1 + 0.35711 B**(1) + 0.17696 B**(2) + 0.21667 B**(3) + 0.08001 B**(4)
                                Moving Average Factors
                             Factor 1:  1 + 0.07162 B**(7)
                                    Input Number 1
                          Input Variable                  load
                          Period(s) of Differencing        1,7
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                                 The ARIMA Procedure
                                    Input Number 1
                          Overall Regression Factor    0.015608
                                 Denominator Factors
                             Factor 1:  1 - 0.59638 B**(1)
```

Appendix (C): About R and SAS

What are R and CRAN?

R is 'GNU S', a freely-available language and environment for statistical computing and graphics which provides a wide variety of statistical and graphical techniques: linear and nonlinear modelling, statistical tests, time series analysis, classification, clustering, etc. These operations have been performed using the R Packages. These collections include functions, data, and compiled code in a well-defined format (R Development Core Team, 2011b; Kabacoff, 2014).

CRAN is a network of ftp and web servers around the world that store identical, up-to-date, versions of code and documentation for R (R Development Core Team, 2011b).

List of R packages in this thesis:

"tseries", "fbasic", "TSA", "fUnitRoots", "urca", "forecast", "fGarch", "urca" "tsDyn", "strucchange", "chron", "ccgarch", "foreign" and "GEVStableGarch".

What is SAS?

SAS is an integrated system of software solutions that enables you to perform the following tasks:

- data entry, retrieval, and management
- report writing and graphics design
- statistical and statistical analysis
- business forecasting and decision support
- operations research and project management
- applications development

How you use SAS depends on what you want to accomplish. Some people use many of the capabilities of the SAS System, and others use only a few. At the core of the SAS System is Base SAS software which is the software product that you will learn to use in this documentation. This section presents an overview of Base SAS. It introduces the capabilities of Base SAS, addresses methods of running SAS, and outlines various types of output.
In over all, base SAS software contains the following:

- a data management facility
- a programming language
- data analysis and reporting utilities

Learning to use Base SAS enables you to work with these features of SAS. It also prepares you to learn other SAS products, because all SAS products follow the same basic rules, (SASInstitute, 2015).

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Summary

Electricity market analysis is important to access strategic market information which can be further employed to pass energy policies. Due to the advantages of privatization, the Iranian government has taken certain fundamental steps in order to construct a competitive market, after passing the pertinent laws in its parliament as to the privatization of the electricity market. This PhD thesis presents a detailed econometric analysis of the Iranian electricity market by means of various approaches of time series analysis. The main idea of this thesis rests on the investigation of the state and degree of competition in the Iranian electricity market using the time series analysis approach.

This research explains Iranian electricity market mechanisms with linear and nonlinear time series statistical approaches. Mechanisms that were previously developed in the Spanish electricity market provide an opportunity to employ time series modeling to further compare the two markets as a benchmark.

This study examines the two indices—price and load—of these markets via time series analysis. In following, it compares these time series analysis in order to present separate estimation models for each index price and load time series (for each market). Implemented models include: linear models (ARIMA), conditional heteroskedastic models (ARMA-GARCH) and nonlinear models (SETAR and ARMA-TGARCH). To assess the best fitted model, MSE and residual volatility analysis tests were implemented. Assuming the conditional variance of our data, the researcher propose the ARMA-TGARCH model as the best suited model for the Iranian electricity market price, ARMA-GARCH model for Iranian electricity load and also for Spanish electricity price and load.

Finally, this research explored the role of load in each market using specific statistical methods such as scatter plots, etc. This study will be quite helpful to establish the state of the Iranian electricity market and how exactly to stimulate its degree of competition. The researcher further suggested that at current state, no significant relationship between price and load in the Iranian electricity market exists. This result led the researcher to examine the impact of other macro and microeconomic factors and indices on the electricity prices in the Iranian market. The most important of these factors have been selected through the study and research of energy markets; the most significant include the Henry Hub Natural Gas Spot Price, Europe Brent Crude Oil Spot Price, the US dollar/Iranian Rial foreign exchange rate, and the Iranian (Tehran) Stock Exchange, specifically the TEPIX. Here, the goal was to survey the potential relationship between these factors and Iranian electricity prices via time series correlation analysis. The researcher also clarified that no significant relationship exists between price and these macro and microeconomic factors in the Iranian electricity market.

The researcher also assembled forecast from the best estimates derived from the study models and carry out simulations to develop forecasting models. This short-term forecasting is applied to both Iranian and Spanish electricity prices and their respective loads. These predictions also clearly showed the different patterns between these indices—price and load—in the Iranian electricity market.

Finally, considering the results obtained through the tests and data analysis which examined the Iranian electricity market, it is concluded that the Iranian electricity market could be still recognized as a non-free/centralized market questioning the claimed policies thus far implemented toward decentralizing and privatizing the Iranian market.