A Novel Soft Computing Approach Based on FIR to Model and Predict Energy Dynamic Systems

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This thesis is dedicated to my father, mother and wife for helping me to be a better person and supporting me to achieve my goals

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Abstract

We are facing a global climate crisis that is demanding a change in the status quo of how we produce, distribute and consume energy. In the last decades, this is being redefined due to: the inclusion of renewable energies and distributed generation; new technologies such as batteries and high-efficient solar panels; and the way the energy is consumed through electric vehicles and new energy habits. All these drivers required a Smart Grid (SG), an intelligent electrical network more observable, controllable, automated and fully integrated with energy services as well as the end-users. Most of the features and proposed SG scenarios are based on reliable, robust and fast energy predictions. For instance, for proper planning activities, such as generation, purchasing, maintenance and investment; for demand side management, such as demand response programs; for energy trading, especially at local level, where productions and consumptions are more stochastics and dynamic; better forecasts also increase grid stability and thus supply security. A large variety of Artificial Intelligence (AI) techniques have been applied in the field of Short-term electricity Load Forecasting (SLF) at consumer level in low-voltage system, showing a better performance than classical techniques. Inaccuracy or failure in the SLF process may be translated not just in a non-optimal (low prediction accuracy) solution but also in frustration of end-users, especially in new services and functionalities that empower citizens. In this regard, some limitations have been observed in energy forecasting models based on AI such as robustness, reliability, accuracy and computation in the edge.

This research proposes and develops a new version of Fuzzy Inductive Reasoning (FIR), called Flexible FIR, to model and predict the electricity consumption of an entity in the low-voltage grid with high uncertainties, and information missing, as well as the capacity to be deployed either in the cloud or locally in a new version of Smart Meters (SMs) based on Edge Computing (EC). FIR has been proved to be a powerful approach for model identification and system's prediction over dynamic and complex processes in different real world domains but not yet in the energy domain. Thus, the main goal of this thesis is to demonstrate that a new version of FIR, more robust, reliable and accurate can be a referent Soft Computing (SC) methodology to model and predict dynamic systems in the energy domain and that it is scalable to an EC integration.

The core developments of Flexible FIR have been an algorithm that can cope with missing information in the input values, as well as learn from instances with Missing Values (MVs) in the knowledge-based, without compromising significantly the accuracy of the predictions. Moreover, Flexible FIR comes with new forecasting strategies that can cope better with loss of causality of a variable and dispersion of output classes than classical *k* nearest neighbours, making the FIR forecasting process more reliable and robust. Furthermore, Flexible FIR addresses another major challenge modelling with SC techniques, which is to select best model parameters. One of the most important parameters in FIR is the number *k* of nearest neighbours to be used in the forecast process. The challenge to select the optimal *k*, dynamically, is addressed through an algorithm, called KOS (K nearest neighbour Optimal Selection), which has been developed and tested also with real world data. It computes a membership aggregation function of all the neighbours with respect their belonging to the output classes. While with KOS the optimal parameter *k* is found online, with other approaches such as genetic algorithms or reinforcement learning is not, which increases the computational time.

These improvements make Flexible FIR fit very well into scenarios of EC, where streaming edge analytics, must be reliable, robust and small enough to fit and run on an IoT gateway or an even smaller device, next to or even on the actual machine. Also when there is not consistent connectivity and is not possible to make use of cloud computing, for instance to tune model's parameters. Following this idea, the concept of a Second Generation SMs based on EC has been proposed under this thesis, which integrates Flexible FIR as energy prediction module running on

the edge and an EC agent with capabilities for trading locally produced renewable energy with a novel mechanism called NRG-X-Change that uses a new decentralized digital currency for energy exchange, called NRGcoin.

Resum

Ens trobem davant una crisis climàtica global que exigeix un canvi del *status quo* de la manera que produïm, distribuïm i consumim energia. En les darreres dècades, aquest *status quo* està sent redefinit degut a: la penetració de las energies renovables i la generació distribuïda; noves tecnologies com bateries i panells solar amb alts rendiments; i la forma en que es consumeix l'energia, per exemple, a través dels vehicles elèctrics o amb l'electrificació de les llars. Aquestes palanques requereixen una xarxa elèctrica intel·ligent (SG: *Smart Grid*) amb major observabilitat, control, automatització i que estigui totalment integrada amb nous serveis energètics, així com amb els seus usuaris finals. La majoria de les funcionalitats i escenaris de les xarxes elèctriques intel·ligents es basen en prediccions de la càrrega elèctrica confiables, robustes i ràpides. Per exemple, per activitats de planificació como la generació, compra, manteniment i inversions; per la gestió de la demanda, com els programes de *demand response*; en el *trading* d'electricitat, especialment a nivell local, on les produccions i els consums són mes estocàstics i dinàmics; una millor predicció elèctrica també augmenta l'estabilitat de la xarxa i, per tant, millora la seguretat. Per les prediccions de càrregues elèctriques a curt termini (SLF: *Short-term electricity Load Forecasting*), a nivell de consumidors al baix voltatge, s'han aplicat una gran varietat de tècniques d'Intel·ligència Artificial (IA) mostrant millor rendiment que tècniques estadístiques tradicionals. Un baix rendiment en els models predictius, pot traduir-se no només en una solució no-òptima (baixa precisió de predicció) sinó també en la frustració dels usuaris finals, especialment en nous serveis i funcionalitats que empoderarien als ciutadans. En aquest sentit, s'han identificat limitacions en models de predicció d'energia basat en IA, com ara robustesa, fiabilitat, precisió i computació a la vora.

En el marc d'aquesta investigació es proposa i desenvolupa una nova versió de la metodologia del Raonament Inductiu Difús (FIR: *Fuzzy Inductive Reasoning*), que hem anomenat Flexible FIR, capaç de modelar i predir el consum d'electricitat d'una entitat amb un grau d'incertesa molt elevat i inclús amb importants carències d'informació (*missing values*). A més, Flexible FIR té la capacitat de desplegar-se al núvol, així como localment, en el que podria ser una nova versió de *Smart Meters* (SM) basada en tecnologia d'*Edge Computing* (EC). FIR ja ha demostrat ser una metodologia molt potent per la generació de models i prediccions en processos dinàmics en diferents àmbits, però encara no en el de l'energia. Per tant, l'objectiu principal d'aquesta tesis és demostrar que una versió millorada de FIR, més robusta, fiable i precisa pot consolidar-se com una metodologia *Soft Computing* (SC) de referencia per modelar i predir sistemes dinàmics en aplicacions per al sector de l'energia i que és escalable a una integració d'EC.

Les principals millores de Flexible FIR han estat, en primer lloc, el desenvolupament i test d'un algorisme capaç de processar els valors d'entrada d'un model FIR tot i que continguin *Missing Values* (MV). Addicionalment, aquest algorisme també permet aprendre d'instàncies amb MV en la matriu de coneixement d'un model FIR, sense comprometre de manera significativa la precisió de les prediccions. En segon lloc, s'han desenvolupat i testat noves estratègies per a la fase de predicció, comportant-se millor que els clàssics k veïns més propers quan ens trobem amb pèrdua de causalitat d'una variable i dispersió en les classes de sortida, aconseguint un procés d'aprenentatge i predicció més confiable i robust. En tercer lloc, Flexible FIR aborda un repte molt comú en tècniques de SC: l'òptima parametrització del model. En FIR, un dels paràmetres més determinants és el número k de veïns més propers que s'utilitzaran durant la fase de predicció. La selecció del millor valor de k es planteja de manera dinàmica a través de l'algorisme KOS (*K nearest neighbour Optimal Selection*) que s'ha desenvolupat i testat també amb dades reals. L'algoritme calcula una funció de pertinença agregada, de tots els veïns, respecte la seva pertinença a les classes de sortida. Mentre que amb KOS el paràmetre òptim de k es calcula *online*, altres enfocaments mitjançant algoritmes genètics o aprenentatge per reforç el càlcul és *offline*,

incrementant significativament el temps de resposta, sent a més a més difícil la implantació en escenaris d'EC.

Aquestes millores fan que Flexible FIR es pugui adaptar molt bé en aplicacions d'EC, on l'anàlisi de dades en *streaming* ha de ser fiable, robusta i amb un model suficientment lleuger per ser executat a un *IoT Gateway* o dispositius més petits. També, en escenaris amb poca connectivitat on l'ús de la computació al núvol no és possible o és limitada i els paràmetres del model es calculen localment. Amb aquestes premisses, en aquesta tesis, es proposa el concepte d'un SM de segona generació basat en EC, que integra Flexible FIR com mòdul de predicció d'electricitat executant-se en el propi dispositiu i un agent EC amb capacitat per el *trading* d'energia produïda localment. Aquest agent executa un innovador mecanisme basat en incentius, anomenat NRG-X-Change que utilitza una nova moneda digital descentralitzada per l'intercanvi d'energia, que s'anomena NRGcoin.

Resumen

Estamos ante una crisis climática global que exige un cambio del *status quo* de la manera que producimos, distribuimos y consumimos energía. En las últimas décadas, este *status quo* está siendo redefinido debido a: la penetración de las energías renovables y la generación distribuida; nuevas tecnologías como baterías y paneles solares con altos rendimientos; y la forma en que se consume la energía, por ejemplo, a través de vehículos eléctricos o con la electrificación de los hogares. Estas palancas requieren una red eléctrica inteligente (SG: *Smart Grid*) con mayor observabilidad, control, automatización y que esté totalmente integrada con nuevos servicios energéticos, así como con sus usuarios finales. La mayoría de las funcionalidades y escenarios de las redes eléctricas inteligentes se basan en predicciones de la energía confiables, robustas y rápidas. Por ejemplo, para actividades de planificación como la generación, compra, mantenimiento e inversión; para la gestión de la demanda, como los programas de *demand response*; en el *trading* de electricidad, especialmente a nivel local, donde las producciones y los consumos son más estocásticos y dinámicos; una mejor predicción eléctrica también aumenta la estabilidad de la red y, por lo tanto, mejora la seguridad. Para las predicciones eléctricas a corto plazo (SLF: *Short-term electricity Load Forecasting*), a nivel de consumidores en el bajo voltaje, se han aplicado una gran variedad de técnicas de Inteligencia Artificial (IA) mostrando mejor rendimiento que técnicas estadísticas convencionales. Un bajo rendimiento en los modelos predictivos, puede traducirse no solamente en una solución no-óptima (baja precisión de predicción) sino también en frustración de los usuarios finales, especialmente en nuevos servicios y funcionalidades que empoderan a los ciudadanos. En este sentido, se han identificado limitaciones en modelos de predicción de energía basados en IA, como la robustez, fiabilidad, precisión i computación en el borde.

En el marco de esta investigación se propone y desarrolla una nueva versión de la metodología de Razonamiento Inductivo Difuso (FIR: *Fuzzy Inductive Reasoning*), que hemos llamado Flexible FIR, capaz de modelar y predecir el consumo de electricidad de una entidad con altos grados de incertidumbre e incluso con importantes carencias de información (*missing values*). Además, Flexible FIR tiene la capacidad de desplegarse en la nube, así como localmente, en lo que podría ser una nueva versión de *Smart Meters* (SM) basada en tecnología de *Edge Computing* (EC). En el pasado, ya se ha demostrado que FIR es una metodología muy potente para la generación de modelos y predicciones en procesos dinámicos, sin embargo, todavía no ha sido demostrado en el campo de la energía. Por tanto, el objetivo principal de esta tesis es demostrar que una versión mejorada de FIR, más robusta, fiable y precisa puede consolidarse como metodología *Soft Computing* (SC) de referencia para modelar y predecir sistemas dinámicos en aplicaciones para el sector de la energía y que es escalable hacia una integración de EC.

Las principales mejoras en Flexible FIR han sido, en primer lugar, el desarrollo y testeo de un algoritmo capaz de procesar los valores de entrada en un modelo FIR a pesar de que contengan *Missing Values* (MV). Además, dicho algoritmo también permite aprender de instancias con MV en la matriz de conocimiento de un modelo FIR, sin comprometer de manera significativa la precisión de las predicciones. En segundo lugar, se han desarrollado y testeado nuevas estrategias para la fase de predicción de un modelo FIR, comportándose mejor que los clásicos *k* vecinos más cercanos ante la pérdida de causalidad de una variable y dispersión de clases de salida, consiguiendo un proceso de aprendizaje y predicción más confiable y robusto. En tercer lugar, Flexible FIR aborda un desafío muy común en técnicas de SC: la óptima parametrización del modelo. En FIR, uno de los parámetros más determinantes es el número *k* de vecinos más cercanos que se utilizarán en la fase de predicción. La selección del mejor valor de *k* se plantea de manera dinámica a través del algoritmo KOS (*K nearest neighbour Optimal Selection*) que se ha desarrollado y probado también con datos reales. Dicho algoritmo calcula una función de

membresía agregada, de todos los vecinos, con respecto a su pertenencia a las clases de salida. Mientras que con KOS el parámetro óptimo de *k* se calcula *online*, otros enfoques mediante algoritmos genéticos o aprendizaje por refuerzo, el cálculo es *offline* incrementando significativamente el tiempo de respuesta, siendo además difícil su implantación en escenarios de EC.

Estas mejoras hacen que Flexible FIR se adapte muy bien en aplicaciones de EC, en las que la analítica de datos en *streaming* debe ser fiable, robusta y con un modelo suficientemente ligero para ser ejecutado en un *IoT Gateway* o dispositivos más pequeños. También, en escenarios con poca conectividad donde el uso de la computación en la nube es limitado y los parámetros del modelo se calculan localmente. Con estas premisas, en esta tesis, se propone el concepto de un SM de segunda generación basado en EC, que integra Flexible FIR como módulo de predicción de electricidad ejecutándose en el dispositivo y un agente EC con capacidad para el *trading* de energía producida localmente. Dicho agente ejecuta un novedoso mecanismo basado en incentivos, llamado NRG-X-Change que utiliza una nueva moneda digital descentralizada para el intercambio de energía, llamada NRGcoin.

Contents

Acronyms

AI: Artificial Intelligence

AMI: Advance Metering Infrastructure

ANFIS: Adaptive Neuro-Fuzzy Inference System

ANN: Artificial Neural Networks

AR-Net: Autoregressive Neural Networks

CI: Computational Intelligence

CNN: Convolutional Neural Network

DL: Deep Learning

DSM: Demand Side Management

DR: Demand Response

DSO: Distribute System Operators

EA: Evolutionary Algorithm

EC: Edge Computing

EPM: Energy Prediction Models

ES: Expert System

ESCO: Energy Service Companies

ESVM: Evolutionary Support Vector Machines

FIR: Fuzzy Inductive Reasoning

FL: Fuzzy Logic

FO: Fuzzy Optimization

FSP: Feature Selection Process

GA: Genetic Algorithm

HEMS: Home Energy Management System

IT: Information Technology

kNN: k Nearest Neighbours

KOS: K nearest neighbour Optimal Selection

LET: Local Energy Trading

LLF: Long-term Load Forecast

MAPE: Mean Absolute Percentage Error

ML: Machine Learning

MLF: Mid-term Load Forecast

MLP-NN: Multi-Layer Perceptron Neural Network

MV: Missing Value / Missing Information / Missing Data

NGSMs: Next Generation of Smart Meters

NMSE: Normalised Mean Squared Error

NWP: Numerical Weather Prediction

PCA: Principal Component Analysis

RBF: Radial Basis Function

RNN: Recurrent Neural Networks

RF: Random Forest

RL: Reinforcement Learning

SC: Soft Computing

SG: Smart Grid

SGSM: Second Generation of Smart Meter

SLF: Short-term Load Forecast

SM: Smart Meter

SVM: Supported Vector Machines

VPP: Virtual Power Plant

Chapter 1: Introduction

This chapter provides the main motivations of this Ph.D. thesis, the reasons why the Fuzzy Inductive Reasoning (FIR) has been chosen as the central methodology to perform this research and the main goals and contributions of the thesis, grouped in Soft Computing (SC) goals and Smart Grid (SG) goals.

1.1 Motivation of the thesis

In the last decade the energy sector is experiencing the biggest challenges since the electrification of Europe. We are facing a global climate crisis caused by the action over the last century of the human race. In its Fifth Assessment Report [1], the Intergovernmental Panel on Climate Change, a group of 1,300 independent scientific experts from countries all over the world under the auspices of the United Nations, concluded there's a more than 95 percent probability that human activities over the past 50 years have warmed our planet.

The industrial activities that our modern civilization depends upon have raised atmospheric carbon dioxide levels from 280 parts per million to 400 parts per million in the last 150 years. The panel also concluded there's a better than 95 percent probability that human-produced greenhouse gases such as carbon dioxide, methane and nitrous oxide have caused much of the observed increase in Earth's temperatures over the past 50 years.

It is clear that one of the main drivers to reduce the impact of the climate crisis is changing the status quo of how we produce, distribute and consume energy. In the last decades, this is being redefined due to the inclusion of renewable energies, new technologies such as batteries and the way the energy is consumed; electric vehicles, new energy habits and so on.

All these drivers required a modernization of the electricity grid and to unlock new services that allows more interaction with the grid. This is what is known as Smart Grid (SG). A SG is an intelligent electrical network used for improving efficiency, sustainability, flexibility, reliability and security of the electrical system by enabling the grid to be observable, controllable, automated and fully integrated [2]-[4]. It allows a seamless and easy connection of distributed energy resources (home batteries, prosumers, wind turbines, etc.) to the grid.

Nowadays, it is a priority of many governments worldwide to replace/upgrade old electricity grids from several decades ago with SG. According to the International Energy Agency, SG investments grew by 10% in 2018 and the deployment and integration service segment is expected to fuel remunerative growth of the global SG industry over the forthcoming years [5]. The Asia Pacific smart grid market is set to grow over 12% by 2024. High transmission and distribution losses, rising electricity thefts and aging grid infrastructure will entail significant deployment of the SG across diverse utilities. Stringent regulatory requirements aimed at reducing carbon emissions and energy consumption will further boost product demand. A new report by global energy market research firm Northeast Group, projects India to invest $44.9 billion in SG infrastructure between 2017 and 2027 [6]. In the US Annual SG investments rose 41% between 2014 and 2016, from $3.4 billion to $4.8 billion, and are expected to rise to $13.8 billion in 2024 [7], while the Chinese government has spent already more than $45billion for its three-stage SG program [8].

The enhancement of the current electricity grids is needed not only in terms of power systems engineering, telecommunications, and cybersecurity, but also core concepts that were not taken into account in past approaches, such as distributed intelligence, automation and information exchange, that will require algorithms and mechanisms that can solve problems involving a large number of highly heterogeneous actors each with their own aims and objectives, having to operate within significant levels of uncertainty and dynamism.

Distributed Intelligence is one of the major driving forces behind a SG, and various Information Technology (IT) systems and disciplines such as artificial intelligence, high performance computing, simulation and modelling, data network management, database management and data mining could be used to facilitate smooth running of the SG [9].

Therefore, a huge gap exists between the SG and outcomes expected that has to be covered in the next years by the combination of experts in the IT, Artificial Intelligence (AI) and energy domain creating technologies that support these new scenarios with: (i) Novel optimisation algorithms for the energy distribution, (ii) Total control: enhancement of the monitor and control over the electricity grid and (iii) Technologies for the local production and distribution.

Most of the features and proposed scenarios are based on reliable, accurate and fast energy predictions. For example, distributed demand and supply relies on knowing the individual consumption and/or production of public and private buildings, industries, and distribute production resources. Moreover, inadequate load and generation forecasting at distribution level has been identified by the European Commission as a main barrier to fulfil system and grid needs for flexibility [10]. The importance of improved load forecasting is also reflected in increasing requirements on forecasting, as laid down in EU network codes, e.g. the Generation & Load Data Provisioning Methodology: GLDPM [11].

Some of the predictions proposed in the literature are based on architectonic features such as heat loss surface, building shape factor, building heated volume and so on [12][13], or housing type and socioeconomic features such as age of the dwelling, size of the dwelling, monthly household income, number of household members, etc. [14]. However, the cost for extracting this information is very high in terms of personnel and tools. Moreover, this information can only be obtained by intrusive methods, i.e. polls at households.

Nevertheless, due to the massive deployment of Smart Meters (SMs), as part of the SG development roadmap, a huge amount of data is collected. Energy companies have access to electricity consumption and/or production with accuracy of minutes, in neighbourhood, dwelling, public building, etc. Therefore, massive data can be collected to train AI forecasting models. This approach is more scalable, non-intrusive and more accurate than traditional forecasting approaches.

To take advantage on the data generated by the SMs and the improvement of these devices with new functionalities are two of the main goals of this thesis.

A large variety of AI techniques have been applied in the field of Short-term electricity Load Forecasting (SLF), showing a better performance than classical techniques. Specifically, Machine Learning (ML) and SC techniques have been proven to accurately predict electric consumption under uncertainties [15][17].

This thesis tries to addresses these challenges by means of Fuzzy Inductive Reasoning (FIR). Although its popularity is not comparable to Artificial Neural Networks (ANN) or Supported Vector Machines (SVM), FIR has been proved to be a powerful approach for model identification and system's prediction over dynamic and complex processes in different real world domains, i.e. medicine [18], fault detection and diagnosis [19], e-learning [20], etc. Its advantage compared to other SC techniques is that i) FIR has achieved a high capacity to deal with uncertainty, ii) it is entirely based on patterns, therefore, it is not needed to understand the system under study and iii) unlike ANN, FIR can provide a justification of the prediction made on the basis of the qualitative states of the input variables selected. Nevertheless, this is the first time

FIR is used in the energy domain and for online SG applications and some weaknesses have been identified. To cope with it, we propose a new version of FIR called Flexible FIR, which has been proven to be more robust and reliable when missing information is present during the training and/or prediction phase. In addition, Flexible FIR has the capacity to auto-tune some of the parameters in the forecasting phase, which is translated in an improvement in the forecasting accuracy.

We visualise some of the previous AI models integrated in a new generation of SMs. They must provide citizens new ways to interact with the energy markets and services that helps the society to achieve the challenging energy goals we have in the next 20 years. SMs are in a unique position to technologically enable new features such as energy trading strategies for a local peer-to-peer in neighbourhoods and communities. However, if we want to increase local production and allow for Local Energy Trading (LET), we need new hardware and software implementations. We believe that this has to be addressed from a decentralized point of view, for example with an Edge Computing (EC) approach. A key component inside the new SMs will be the Energy Prediction Module (EPM), because it has to provide not only accurate predictions to the Distribute System Operator (DSO) but also robust and reliable forecasting for the individual (agent) participating in a local energy markets to achieve an optimal solution. to the agent collaborating in a local energy market.

This thesis tries to address these challenges through the conceptualization of a Second Generation of Smart Meter (SGSM) based on EC with Flexible FIR as EPM and an agent with capabilities for trading locally produced renewable energy.

1.2 Methodology selection

The FIR methodology is the one chosen as the basis to perform the AI research contributions addressed in this thesis due to some of its main advantages:

- This methodology of modelling and simulation has the ability to describe systems that cannot be easily described by classical mathematics or statistics, i.e. systems for which the underlying physical laws are not well understood
- The technique can be applied to any system available for testing and observation. The inductive reasoning is entirely based on patterns; therefore, it is not necessary to know the internal structure of the system under study. In this regard, the inductive reasoners are similar to neural networks.
- The methodology contains a model inherent validation mechanism within the simulation method. This mechanism prevents that the model reaches conclusions that cannot be justified on the basis of available data. In this regard, the inductive reasoners are similar to knowledge-based systems.
- Inductive reasoning operates in a qualitative form, as the knowledge-based reasoners do, and is able to provide information on the subset of causal and spatial relationships established between the variables used in the reasoning process, and can provide a justification of the prediction made on the basis of the qualitative states of the input variables selected.
- It has already been proven the great capacity of this methodology for model identification and system's simulation/prediction over dynamic and complex processes in different real world domains.
- FIR has achieved a high capacity to deal with uncertainty, very common in real world problems, especially in complex datasets.

1.3 Thesis objectives

The main goal of this thesis is to demonstrate that a new version of FIR, more robust, reliable and accurate can be a referent SC methodology to model and predict dynamic systems in the energy domain, such as but not limited to libraries, classrooms and administrative buildings, and that it is scalable to an EC integration.

Due to the nature of most of SG applications, this framework should be robust, fast and reliable enough to predict the energy consumption of an entity with high uncertainties, and information missing, as well as the capacity to be deployed either in the cloud or locally in a new version of SMs or concentrators, generally known as EC.

Therefore, the main goals of the thesis can be divided in the following sub-objectives:

1.3.1 Soft Computing goals

1. To demonstrate that FIR is as good as other ML and SC techniques to address energy forecasting scenarios.
2. To investigate entropy-based feature selection combined with ML and SC techniques
3. To design and develop aa new version of FIR, named Flexible FIR, which can cope with missing information in the input values, as well as during the prediction phase.
4. To enhance Flexible FIR prediction process with different output forecast strategies, which are not highly affected by the dispersion of the output classes and preserves confidence in prediction.
5. Design and development of a *k* parameter selection algorithm to be used dynamically during the Flexible FIR prediction phase.

1.3.2 Smart Grid goals

6. To demonstrate the performance of hybrid methodologies for electricity load forecasting modelling, at consumer level connected to low-voltage systems, and their scalability for different consumption profiles.
7. To improved demand-side management in industry, households and public buildings by predicting better short-term electricity consumptions.
8. To propose a new generation of SMs, based on an EC and implementing Flexible FIR as AI module and novel trading mechanisms.

1.4 Contributions of the thesis and derived articles

In this section, a more detailed description of each goal is provided and the articles derived out of each objective are presented.

<u>Contribution 1:</u> **To demonstrate that FIR is as good as other ML and SC techniques to address energy forecasting scenarios**

Large scale studies for comparing ML and SC tools have focused on the classification domain. On the contrary, a very few extensive studies can be found in the regression domain. There are actually studies that compare ML or SC techniques, but very few comparing between each other and none comparing with FIR.

For this objective different AI consolidated methodologies, i.e. Random Forest (RF), Autoregressive Neural Networks (AR-Net), Evolutionary Support Vector Machines (ESVM) and FIR, are proposed and compared to perform short-term electric load forecasting. This is the first study where FIR is compared to other regression techniques in the energy domain.

Based on this study, it is found that FIR is the methodology that performs a better forecast followed by RF, ESVM and AR-Net. From the results it can be concluded that FIR is a promising methodology for the task of predicting electric load and, therefore, should be studied more deeply.

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S. Jurado, J. Peralta, A. Nebot, F. Mugica, and P. Cortez, "Short-term electric load forecasting using computational intelligence methods", FUZZ-IEEE 2013: IEEE International Conference on Fuzzy Systems, Hyderabad, India, pp. 1-8, 2013. doi: 10.1109/FUZZ-IEEE.2013.6622523.

Contribution 2: **To investigate entropy-based feature selection combined with ML and SC techniques**

and

Contribution 6: **To demonstrate the performance of hybrid methodologies for electricity load forecasting modelling and their scalability for different consumption profiles**

Here we design hybrid methodologies such as FIR, which are based on entropy-based feature selection, with other techniques, i.e. RF and ANN. We demonstrate their ability to perform short-term electric load forecasting (24 h) in several types of buildings. To do so, three functional zones of the UPC are used in the experiments. They all have different profiles of usage and locations, thus, affecting different climatology, consumption patterns, schedules and working days.

The hybrid methodologies are designed in two stages: 1) a Feature Selection Process (FSP) based on Entropy, common to all three methodologies and 2) a FIR, RF or ANN model training process.

A first set of experiments and its results were published as a book chapter in Frontiers in Artificial Intelligence and Applications:

S. Jurado, J. Peralta, A. Nebot, F. Mugica and N. Avellana. "Towards the Development of the Smart Grid: Fast Electricity Load Forecasting Using Different Hybrid Approaches", Frontiers in Artificial Intelligence and Applications (16th International Conference of the Catalan Association for Artificial Intelligence), vol. 256, pp. 185-188, 2013.

We wanted to investigate more deeply and to understand how the model's accuracy is affected by the most relevant parameters, obtained by means of the FSP. To do so, we have studied the prediction errors versus the number of most important variables and the time depth involved. We have also added and additional model comparison with ARIMA, which helps to compare them with a traditional time series forecasting statistic technique.

In general, AI methodologies adapt better to consumption changes when they perform the predictions, following the real shape of the curve, detecting better the peaks and achieving very low prediction errors. With regards to ARIMA, it is a more conservative methodology, which does not produce high errors but the accuracy is far from FIR.

Finally, as for the computational cost, all the methodologies are very fast in order to obtain the model (less than 10 sec. for a training set of a year hourly data) and perform a prediction. On the contrary, the FSP increases considerably with the time depth and the number of past values selected. However, this is an offline process that could be performed for instance in the cloud.

The performance of these hybrid methodologies for electricity load forecasting and their scalability for different consumption profiles has been widely experimented resulting in a publication in the journal Energy:

S. Jurado, A. Nebot and F. Mugica, "Hybrid methodologies for electricity load forecasting: Entropy-Based Feature Selection with Machine Learning and Soft Computing Techniques", Energy, vol. 86, pp. 276-291, 2015. http://dx.doi.org/10.1016/j.energy.2015.04.039

Contribution 3: **To design and develop a new version of FIR, named Flexible FIR, which can cope with missing information in the input values, as well as during the prediction phase**

Robustness under uncertainties is one of the major goals of this thesis. Missing Values (MVs) can dramatically affect the performance of the energy forecasting or distort the prediction significantly. Thus, accuracy and reliability of the predictions must be guaranteed.

A model in FIR methodology is composed of the mask (i.e. model structure) and a set of rules, called pattern rule base (i.e. behaviour matrix). The mask defines the causal and temporal relations between the inputs and output variables, i.e. it contains the variables selected as relevant. Once the best mask has been identified, it can be applied to the qualitative data obtained from the system resulting in a particular pattern rule base, which is a set of rules that represent pseudo-static relationships and that contains the system's behaviour.

While FIR displays high prediction accuracy in complex systems, it has several limitations when missing data are present in the forecasting process. For example, for a qualitative data set of 358 registers containing 24 consecutive MVs and a mask depth of 168, it is possible to generate up to 191 pattern rules that contain at least one missing element. This can become a huge problem due to the fact that the current prediction process of FIR methodology discards the pattern rules containing MVs, and, therefore, the valid pattern rule base available is reduced significantly. This implies that FIR prediction process, very often, is not able to predict a new input pattern due to the fact that it does not exist in the behaviour matrix.

In addition to this problem, there is a second weakness of FIR when it faces MVs. In concrete, when the input pattern contains MVs. It may happen, especially with online predictions that the input pattern generated after the fuzzification contains MVs. In SG applications, there are different reasons why the information feed into the model may contain MVs: failure in the communication between the SM and the concentrator, the battery of a home area sensor is depleted, loss of internet connection, etc.

The enhancement proposed is to design an algorithm that makes the inference process flexible in a dynamic way. The idea is to use the traditional FIR algorithm, when there exist in the behaviour matrix rules that have the same input pattern (free of MVs) than the one to be predicted. When this is not the case, the algorithm will select the set of pattern rules that have the same input pattern but relaxing one of its inputs. That is, the same input pattern but allowing that one of the inputs is missing.

This new version of FIR has been called Flexible FIR and was presented in:

S. Jurado, A. Nebot and F. Mugica, "A flexible fuzzy inductive reasoning approach for load modelling able to cope with missing data", International Conference on Simulation Tools and Techniques. SIMUTools '15: proceedings of the 8th International Conference on Simulation Tools and Techniques, Athens, Greece, pp. 349-356, 2015.

In addition, we have evaluated the implications in prediction accuracy and number of instances predicted, when the number of MVs in the training dataset is increased progressively. With this objective we have been able to decrease dramatically the situations where FIR could not predict due to MVs with a good compromise in accuracy. This is a remarkable contribution because increases the robustness of the methodology and could help, for instance, in load modelling applications where missing data is present in online predictions.

The results were published in the journal Applied Soft Computing:

S. Jurado, A. Nebot, F. Mugica and M. Mihaylov, "Fuzzy inductive reasoning forecasting strategies able to cope with missing data: A smart grid application", Applied Soft Computing, vol. 51, pp. 225-238, 2017.

Contribution 4: **To enhance Flexible FIR prediction process with different output forecast strategies, which are not highly affected by the dispersion of the output classes and preserves confidence in prediction.**

For the objective 3, a new version of FIR, i.e. Flexible FIR, has been designed and developed. As it has been explained before, when there are no rules in the behaviour matrix equal to the input pattern to be predicted or this input pattern has MVs, the algorithm will select the set of pattern rules that have the same input pattern but relaxing one of its inputs, i.e. allowing that one of the inputs is missing. Basically, this means that we are using a different mask than the one selected by FIR in the modelling process. Therefore, we are ignoring one of the variables selected as relevant in the feature selection process.

The consequences are that we might have a dispersion of the output classes and the confidence in prediction decreases. To solve this issue, seven different FIR forecasting strategies are proposed and studied taking into account several features to perform the prediction: causal relevance of input variables, consistency of predictions, inertia criterion and *k*-Nearest Neighbours (kNN).

We have come up that output forecasting strategies that incorporate causal relevance are able to compensate the loss of causality, therefore, if it is possible to quantify the importance of each m-input with respect to the output, then it is possible to assign a higher weight to those m-inputs with a higher importance.

The results were published in the journal Applied Soft Computing (also referenced in the 3rd contribution):

S. Jurado, A. Nebot, F. Mugica and M. Mihaylov, "Fuzzy inductive reasoning forecasting strategies able to cope with missing data: A smart grid application", Applied Soft Computing, vol. 51, pp. 225-238, 2017.

Contribution 5: **Design and development of a k parameter selection algorithm to be used dynamically during the Flexible FIR prediction phase**

To achieve an accurate, robust and fast prediction, model's parametrization is key and becomes a bottleneck in the value-chain. This is clear in publications of objectives 1 and 2 where we have pointed out the implications of the depth of the mask in prediction accuracy.

Another example is the selection of the *k* value of the kNN process in the prediction phase. The FIR inference engine is based on the kNN approach, commonly used in the pattern recognition field. The forecast of the output variable is obtained by means of composition of the potential conclusion, which results from firing the kNN rules whose antecedents have best matching with the actual state.

To select the most optimal number of nearest neighbours during FIR prediction phase, we have designed an algorithm called K nearest neighbour Optimal Selection (KOS) that works with Standard and Flexible FIR, which is able to decide in each new prediction, the optimal value of the parameter *k*. The idea behind the KOS approach is to perform a kind of membership aggregation function of all the neighbours with respect their belonging to the output classes. The output class that has the higher aggregated value for that specific input pattern is the one that represents better the behaviour of the system. Then, once the output class is selected, the optimal value is the minimum *k* that has the highest aggregated membership value.

The results show that the best forecasting accuracy, on average, is when the KOS is used on Flexible FIR, when compared with the selection of a *k* that keeps its value for all the predicted elements.

Our algorithm helps to decide in each hourly prediction, which is the optimal number of neighbours to compute the next output state in Standard and Flexible FIR approaches. While with KOS the optimal parameter *k* is found online, without it, is not, which increases the computational time.

Therefore, this contribution sheds light on robust SC methodologies for smart home, smart buildings and smart grid applications.

This study was published in IEEE International Conference on Fuzzy Systems, FUZZ-IEEE 2019:

<u>S. Jurado</u>, À. Nebot and F. Mugica, "K Nearest Neighbour Optimal Selection in Fuzzy Inductive Reasoning for Smart Grid Applications", IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), New Orleans, USA, pp. 1-6, 2019. DOI: 10.1109/FUZZ-IEEE.2019.8858961.

We are currently preparing a journal article which presents this contribution and discuss the whole results obtained in the seven buildings studied. The previous publication (FUZZ-IEEE 2019) includes only the results of three of the seven buildings addressed. Appendix I presents the results obtained for the rest of the buildings since we still are working on the journal paper, which is not yet available.

<u>Contribution 7:</u> **To improved demand-side management in industry, households and public buildings by predicting better short-term electricity consumptions.**

Load forecasting in buildings and homes has been in recent years a task of increasing importance. New services and functionalities can be offered to the public and private sector due to this predictions, for instance, the detection of potential demand response programs, peaks that may increase the energy bill in a dynamic tariff framework and additional energy services. In fact, in recent years there has been an increased interest in the provision of energy services to achieve energy and environmental goals. In particular, some new companies providing energy services to final energy users, including the supply and installations of energy efficient equipment, and/or the building refurbishment, have started to operate on the European market.

What characterises these companies, defined as Energy Service Companies (ESCOs) from the traditional energy consultants or equipment suppliers is the fact that they can also finance or arrange financing for the operation and their remuneration is directly tied to the energy savings achieved [21]. In addition, an ESCO offers energy services which may include implementing energy-efficiency projects (and also renewable energy projects) and in many case on a turn-key basis. It is fundamental for these services to rely on accurate energy demand forecasting.

In this thesis we have contributed with three publications in conferences and journals, where for the first time Standard FIR and our improved version Flexible FIR are used for short-term electricity load forecasting with better results compared to other SC and ML techniques.

S. Jurado, J. Peralta, A. Nebot, F. Mugica, and P. Cortez, "Short-term electric load forecasting using computational intelligence methods", FUZZ-IEEE 2013: 2013 IEEE International Conference on Fuzzy Systems, Hyderabad, India, pp. 1-8, 2013. doi: 10.1109/FUZZ-IEEE.2013.6622523.

S. Jurado, J. Peralta, A. Nebot, F. Mugica and N. Avellana. "Towards the Development of the Smart Grid: Fast Electricity Load Forecasting Using Different Hybrid Approaches", Frontiers in Artificial Intelligence and Applications (16th International Conference of the Catalan Association for Artificial Intelligence), vol. 256, pp. 185-188, 2013.

S. Jurado, A. Nebot and F. Mugica, "Hybrid methodologies for electricity load forecasting: Entropy-Based Feature Selection with Machine Learning and Soft Computing Techniques", Energy, vol. 86, pp. 276-291, 2015. http://dx.doi.org/10.1016/j.energy.2015.04.039

Contribution 8: **To propose a new generation of SMs, based on an EC and implementing Flexible FIR as AI module and novel trading mechanisms.**

Before going through this contribution, it is important to mention that part of this research is set within the context of the European project: "SCAlable & modular system for eNERGY trading between prosumers" (1/2/2013 – 31/1/2017), with the collaboration of colleagues of the Vrije Universiteit Brussel.

Nowadays many energy retailers apply feed-in tariffs to motivate prosumers to inject their produced energy. With the rising decentralization of renewable energy production, it is a challenge to offer subsidies that ensure a profitable and balanced grid for all parties involved. There rises the need to design LET mechanism that aligns the objectives of individual prosumers, who are aiming for high profits from their investments, with the objectives of governments seeking long term positive environmental change. In addition, with the high penetration of wind, solar power and customers' active participation have lead LET to operate in more uncertain, complex environments. Currently, EPMs are used to get the user's electricity characteristic curve and required for proper scheduling activities, power systems planning and operations, revenue projection, rate design, energy trading, and so forth. EPMs must be robust and reliable enough to work under uncertain consumer/prosumer behaviour and with intermittent data (missing information), because LET mechanisms heavily rely on predictions.

This evolution towards a system able to manage prosumers, batteries, LET and EPMs, in an efficient and decentralized way, has called for the deployment of more advanced metering systems. Current SMs aims at monitoring several key parameters as power quality, remote service switch, outages, which are helping DSOs in their load forecast process hence in a more effective operation of their grid. The use of SMs helps reduce metering errors and identify fraud, and reduces the gap between peak demand and the available power at any given time as well.

Nevertheless, most of first generation SMs are starting to become outdated. Several important and strictly necessary services, not included in the current generation of SMs, have to be part of them in order to be considered smart devices. Having these features is essential for the evolution towards a system able to manage prosumers, batteries, LET and EPMs in an efficient and decentralized way. From our perspective, this situation has called for the deployment of a Next Generation of Smart Meters (NGSMs). We believe that these devices are meant to orchestrate a set of new functionalities that will bring SG goals to a next level.

We believe in EC as a core technology of the NGSMs. With EC much of the intelligent data processing is done directly on the ground, without the need to send the data to the cloud, which optimizes the reaction time for intelligent decision making. By moving certain workloads to the perimeter of the network, devices waste less time communicating with the cloud, react more quickly to local changes and more reliably, even for prolonged periods without connection. In addition, only a small fraction of the data acquired is significant after analysing it. Send only what is necessary to the cloud, reduce the cost of sending all the data to the cloud and maintain a good quality of them.

In the following position paper, we have addressed the need to develop a new generation of SMs that allows not only the prediction of consumptions and net energy that small producers can provide to the local grid, but also to include an EC agent with trading mechanisms that maximize profits if they participate in the local electricity market. We propose Flexible FIR as cornerstone for the EPM due to its proven reliability and robustness modelling energy dynamic systems and NRG-x-Change and the NRGCoin as trading mechanism of the EC agent.

S. Jurado, A. Nebot, and F. Mugica, "The importance of Robust and Reliable Energy Prediction Models: Next Generation of Smart Meters", SIMULTECH 2020: 10th International Conference on Simulation and Modelling Methodologies, Technologies and Applications, Online Conference due to COVID19, July 2020.

The NRG-X-Change is a novel mechanism for trading of locally produced renewable energy that does not rely on an energy market or matching of orders ahead of time. This mechanism uses a new decentralized digital currency for energy exchange, called NRGcoin, a concept similar to Bitcoin.

Prosumers exchange NRGcoins with fiat currency on an exchange market for profit, or for paying their energy bills. We study the advantages of our proposed currency over traditional monetary payment and explore its benefits for all parties in the smart grid.

Both, NRGcoin and NRG-X-Change have been presented in two conferences related to energy market and trading of renewable energy:

M. Mihaylov, S. Jurado, N. Avellana, K. Van Moffaert, I. Magrans and A. Nowé, "NRGcoin: Virtual Currency for Trading of Renewable Energy in Smart Grids," Proc. of the 11th International Conference on the European Energy Market (EEM), Krakow, Poland, pp. 1-6, 2014.

M. Mihaylov, S. Jurado, K. Van Moffaert, N. Avellana, and A. Nowé, "NRG-X-Change: A Novel Mechanism for Trading of Renewable Energy in Smart Grids," Proc. of the 3rd International Conference on Smart Grids and Green IT Systems (SmartGreens), Barcelona, Spain, pp. 101-106, 2014.

In order to demonstrate in a simulation environment the NRG-x-Change and the NRGCoin concepts, a prototype of NGSM was created, using Raspberry Pi to unlock EC capabilities. Prosumers were represented as software agents running on individual Raspberry Pi boards and consumers' agents where running in individual threads on two Raspberry Pi boards. NGSMs were connected to the Internet, which allows agents to submit orders for buying and selling NRGcoins, i.e. to trade energy, through their smartphones. Orders were matched in real-time using continuous double auction, as employed by the New York Stock Exchange. Agents used an EPM based on RF technique to determine the quantity to trade and the adaptive attitude bidding strategy to determine the bid/ask price. Two short papers describing this simulation were presented on the AAMAS and PAAMS conferences:

M. Mihaylov, S. Jurado, N. Avellana, I. Rázo-Zapata, K. Van Moffaert, A. Cañadas, M. Bezunartea, L. Arco, I. Grau and A. Nowé, "SCANERGY: a Scalable and Modular System for Energy Trading Between Prosumers," Proc. of the 14th International Conference on Autonomous Agents and Multiagent Systems (AAMAS), Istanbul, Turkey, pp. 1917-1918, 2015.

M. Mihaylov, I. Razo-Zapata, R. Rădulescu, S. Jurado, N. Avellana and A. Nowé, "Smart Grid Demonstration Platform for Renewable Energy Exchange", Lecture Notes in Computer Science, (Advances in Practical Applications of Scalable Multi-agent Systems. The PAAMS Collection), vol. 9662, pp. 277-280, 2016.

Finally, a journal publication comparing different incentive mechanisms, including NRG-x-Change for energy trading was developed:

M. Mihaylov, R. Rădulescu, I. Razo-Zapata, S. Jurado, L. Arco, N. Avellana and A. Nowé, "Comparing Stakeholder Incentives Across State-of-the-art Renewable Support Mechanisms", Renewable Energy, vol. 131, pp. 689-699, 2019.

1.5 List of articles derived from the thesis and quality indices

Publications are divided in three groups: journals, book chapters and conferences. For each of these groups the articles are listed by year of publication, from most recent to the least. The quality index of the journals and the conferences, are also specified. A complete copy of the articles is provided separately.

Journals (JCR)

1. M. Mihaylov, R. Rădulescu, I. Razo-Zapata, S. Jurado, L. Arco, N. Avellana and A. Nowé, "Comparing Stakeholder Incentives Across State-of-the-art Renewable Support Mechanisms", ***Renewable Energy***, 2019, vol. 131(C), pp. 689-699.
   https://doi.org/10.1016/j.renene.2018.07.069
   Web of Science Citations: 2; Google Scholar Citations: 6
   JCR Impact factor (last year records 2018): 5.439
   JCR Quartile and rank in the category (last year records 2018):
   Q1 - Green & Sustainable Science & Technology 7/35
   Q1 - Energy & Fuels (17/103)

2. S. Jurado, A. Nebot, F. Mugica and M. Mihaylov, "Fuzzy inductive reasoning forecasting strategies able to cope with missing data: A smart grid application", ***Applied Soft Computing***, 2017, vol. 51, pp. 225-238.
   https://doi.org/10.1016/j.asoc.2016.11.040
   Web of Science Citations: 8; Google Scholar Citations: 15
   JCR Impact factor (2017): 3.907
   JCR Quartile and rank in the category (2017):
   Q1 – Computer Science, Artificial Intelligence (20/134)
   Q1 – Computer Science, Interdisciplinary Applications (11/106)

3. S. Jurado, A. Nebot and F. Mugica, “Hybrid methodologies for electricity load forecasting: Entropy-Based Feature Selection with Machine Learning and Soft Computing Techniques”, ***Energy,*** 2015, vol. 86, pp. 276-291.
   http://dx.doi.org/10.1016/j.energy.2015.04.039
   Web of Science Citations: 60; Google Scholar Citations: 95
   JCR Impact factor JCR (2015): 4.292
   JCR Quartile and rank in the category (2015):
   Q1 – Thermodynamics (3/60)
   Q1 – Energy & Fuels (15/103)

Book Chapters

4. S. Jurado, J. Peralta, A. Nebot, F. Mugica and N. Avellana. “Towards the Development of the Smart Grid: Fast Electricity Load Forecasting Using Different Hybrid Approaches”, *Frontiers in Artificial Intelligence and Applications,* vol. 254, pp. 185-188, 2013.

Conferences

5. S. Jurado, A. Nebot and F. Mugica, “The importance of Robust and Reliable Energy Prediction Models: Next Generation of Smart Meters”, *Simultech’20: 10th International Conference on Simulation and Modelling Methodologies*, Technologies and Applications, Lieusaint-Paris, France, 2020, accepted but under edition and publication.

6. S. Jurado, À. Nebot and F. Mugica, "K Nearest Neighbour Optimal Selection in Fuzzy Inductive Reasoning for Smart Grid Applications", *IEEE International Conference on Fuzzy Systems (FUZZ-IEEE),* New Orleans, USA, 2019. DOI: 10.1109/FUZZ-IEEE.2019.8858961.
   This conference is considered remarkable by the UPC.
   Web of Science Citations: 0; Google Scholar Citations: 1

7. M. Mihaylov, I. Razo-Zapata, R. Rădulescu, S. Jurado, N. Avellana and A. Nowé, "Smart Grid Demonstration Platform for Renewable Energy Exchange", *Advances in Practical Applications of Scalable Multi-agent Systems. The PAAMS Collection. PAAMS 2016. Lecture Notes in Computer Science*, vol 9662. Springer, Cham.
   Web of Science Citations: 8; Google Scholar Citations: 16

8. S. Jurado, A. Nebot, F. Mugica, “A flexible fuzzy inductive reasoning approach for load modelling able to cope with missing data”, *International Conference on Simulation Tools and Techniques. SIMUTools '15: proceedings of the 8th International Conference on Simulation Tools and Techniques,* Athens, Greece, 2015.
   This conference is considered remarkable by the UPC.
   Web of Science Citations: 0; Google Scholar Citations: 2

9. M. Mihaylov, S. Jurado, N. Avellana, I. Rázo-Zapata, K. Van Moffaert, A. Cañadas, M. Bezunartea, L. Arco, I. Grau and A. Nowé, "SCANERGY: a Scalable and Modular System for Energy Trading Between Prosumers," *Proc. of the 14th International Conference on Autonomous Agents and Multiagent Systems (AAMAS),* Istanbul, Turkey, 2015.
   This conference is considered remarkable by the UPC.
   Web of Science Citations: 12; Google Scholar Citations: 26

10. M. Mihaylov, S. Jurado, N. Avellana, K. Van Moffaert, I. Magrans de Abril and A. Nowé, "NRGcoin: Virtual Currency for Trading of Renewable Energy in Smart Grids," *Proc. of the*

11th International Conference on the European Energy Market (EEM), Krakow, Poland, 2014.
Web of Science Citations: 12; Google Scholar Citations: 137

11. M. Mihaylov, S. Jurado, K. Van Moffaert, N. Avellana, and A. Nowé, "NRG-X-Change: A Novel Mechanism for Trading of Renewable Energy in Smart Grids," *Proc. of the 3rd International Conference on Smart Grids and Green IT Systems (SmartGreens)*, Barcelona, Spain, 2014.
Web of Science Citations: 0; Google Scholar Citations: 55

12. S. Jurado, J. Peralta, A. Nebot, F. Mugica, and P. Cortez, "Short-term electric load forecasting using computational intelligence methods", *FUZZ-IEEE 2013: 2013 IEEE International Conference on Fuzzy Systems*, Hyderabad, India, 2013. doi: 10.1109/FUZZ-IEEE.2013.6622523.
This conference is considered remarkable by the UPC.
Web of Science Citations: 1; Google Scholar Citations: 16

1.6 Organization of the document

This document is organized as follows. After this introduction, the state of the art is presented in Chapter 2. The state of the art chapter is organized, first, with an overview of some AI applications in the SG domain, after, we go into detail about energy modelling applications, in concrete, short-term load forecasting techniques.

In Chapter 3 the main conclusions of this thesis are discussed and the future research is outlined.

Chapter 4 contains the list of references and bibliography used in this research.

Finally, an appendix is included where the results obtained by the KOS algorithm that are still not published are presented.

Notice that the post-prints of all the articles derived from this doctoral thesis are provided in a separate folder.

Chapter 2: State of the Art

This chapter provides a review of AI applications in SG since 2000, with special emphasis in the use of SC and ML for energy modelling. Many papers/dissertations have been published, covering AI applications in SG. Several research efforts in this direction can be found in the literature such as [15] focused in Computational Intelligence (CI) applications for SG, [17] a review on the research and practice of Deep Learning (DL) and Reinforcement Learning (RL) in SG or [16] where Merabet et al. performs a survey on Applications of Multi-Agent Systems in SG.

It is not our intention to perform an intensive literature review on AI applications and techniques for SG but to give an overview about the different applications, techniques, approaches and where the contributions in this thesis are located.

2.1 AI applications in Smart Grid

With the development of the SG, high penetration of wind, solar power and customers' active participation have lead SG to operate in more uncertain, complex environments. Traditional power system analysis and control decision making are primarily dependent on physical modelling and numerical calculations. The traditional methods find difficulty in addressing uncertainty and partial observability issues so that they cannot meet the requirements of future development of SG. Currently, AI, as a newly developed scientific technology used to imitate, stretch, and extend the theory, method, technology, and application of human intelligence, is providing a great support for promoting the intelligence revolution of power and energy system. AI technology with attractive features such as DL, cross-border integration, man-machine cooperation, open group intelligence, and autonomous control shows the strong handling capacity in perceptual intelligence, CI, and cognitive intelligence, which shows great potential in reshaping the way of producing and utilizing the electrical energy. In particular, the combination of AI with cloud computing, big data, internet of things (IoT), and mobile interconnection can endow the power system with features of intelligent interaction, safety, and controllability. Thus, the security, reliability, and flexibility of the power grid can be significantly improved. The revolution of the power and energy system can be highly sped up.

These application fields cover demand side management, system planning and market trade, intelligence integration of renewables and image recognition. This section reviews some of the available literature.

2.1.1 Demand Side Management and Demand Response

One of the most well-researched fields of electricity system flexibility is called Demand Side Management (DSM), which aims to improve flexibility on the consumer side and helps utilities to reduce peak load demand and reshape load profile. This results in a reduction of the overall operational cost, carbon emissions levels and increase sustainability of the grid. The implementation of DSM programs can range from improving energy efficiency with better insulation materials to fully autonomous energy systems that automatically respond to shifts in supply and demand. DSM can be implemented in two ways: through energy efficiency or Demand Response (DR) [22]. DR refers to programs that encourage participants to make short-term reductions in energy demand.

The concept of DSM is not new and the first papers date from end 80's early 90's [23][24], however, it has been in the last decade that the technology maturity and business models have been ready. Recent developments in power electronics, communication and automation technologies facilitate implementation of domestic load management methods and also, utilities have defined business models where end-users have economic incentives, i.e. DR programs.

Most of the existing DSM strategies used in traditional energy management systems employ system specific techniques and algorithms. Most of the techniques were developed using dynamic programming [25] and linear programming [26][27]. These programming techniques cannot handle a large number of controllable devices from several types of instruments which have several computation patterns and heuristics. In addition, the unpredictability of renewable energy sources makes power dispatch functions in a smart grid challenging. Such scenarios need the use of more advanced load control methodologies based on AI.

In [28] an heuristic-based Evolutionary Algorithm (EA) that easily adapts heuristics in the problem was developed for solving this minimization problem. Simulations were carried out on a SG which contains a variety of loads in three service areas, one with residential customers, another with commercial customers, and the third one with industrial customers. The simulation results show that the proposed demand side management strategy achieves substantial savings, while reducing the peak load demand of the smart grid.

Fuzzy Logic (FL) has been used in [29] to provide operation modes with different levels of intrusion in the decision making in the different automated loads. In the development of the modes of operation they sought to create rules that prioritize the use of the electric energy generated by the photovoltaic system. With this, there is the least injection of excess electric power in the grid.

This technique has been also used in controllers for domestic load management in DR programs. In [30] three optimization parameters, i.e. comfort, cost and demand response are taken into account. Simulation results show that the proposed controller successfully limits the power consumption during the peak hours and concurrently maximizes the savings of energy consumption cost without violating consumers' comfort level. Similarly, Keshtkar et al. [31] simulate a Programable Communicating Thermosat to control HVAC systems (heating, ventilation, and an air-conditioning) with a FL approach embedded into the PCT. In this study the optimization parameters are Time-Of-Use and Real-Time Pricing. Results show energy and cost saving in residential buildings versus existing Programable Communicating Thermosats.

DL has been used by Marques [32] to identify the flexibility of loads, and to provide references for demand response. In [33] the authors use factored four way conditional Restricted Boltzmann Machines (RBM) to identify and predict flexibility in real time. Paper [34] uses Recurrent Neural Networks (RNN) to classify consumers and proves that the proposed algorithms can have better performances than the existing methods; in some cases the new calculated rates can reach nearly 100%.

RL is another AI technique well-used in DSM for intelligent bidding strategies. In papers [35][36], RL is applied for the setting of residential demand response at the device level while in papers [37] and [38], RL is used in an aggregate-and-dispatch setting with thermostatically controlled loads. Another recent example where RL is used for residential DSM is in [39]. Li et al. investigate an integrated Home Energy Management System (HEMS) that participates in a DSM program and is equipped with an EC server. The HEMS aims to maximize the home owner's expected total reward. The particular DSM program considered in this paper, which is a widely-adopted one, requires the household to reduce certain amount of energy consumption within a specified time window. In contrast to well-studied real-time pricing, such a DSM program results in a long-term temporal interdependency (i.e., of a few hours) and thus high-dimensional state space in their formulated Markov decision processes. To address this challenge, they use DRL to solve the problem. Experiments show that the proposed scheme achieves significant performance gains over reasonable baselines. Several other studies of RL in DR applications can be found in [17].

DL, as a data driven approach, can be used to extract the load's characteristics, and RL, also a model free method, can support aggregator, customers and grid operators to make decisions for demand response. Nevertheless, how to analyse flexibility from the customer side, control load directly, and make decisions for all the stakeholders in demand response, especially under the partial observability environments, are still open questions.

2.1.2 Intelligent optimization and its application in market trade and electric power system

Market Trade

Trading of locally produced renewable energy is addressed in literature from a market perspective and under multiagent based techniques, where prosumers and consumers (or collectively: agents) participate in a double auction and trade energy on a day-ahead basis [40]-[45]. Buy and sell orders for energy are submitted to a public orderbook and orders are matched either in a continuous fashion [43][44] or at discrete market closing times using the equilibrium price [41][45]. The advantages of this market-based control concept are that it achieves close to optimal allocation, neatly balances supply and demand and aligns the preferences of self-interested agents.

Bidding for energy ahead of time relies heavily on predictions of future supply or demand, for instance, in a recent study [46], the Local Coordination Agent performs very short-term forecasting to predict the power generation and consumption over future n time interval. Although the forecasting method itself is not the focus of the study, it relies on these predictions and the inaccuracy of which translates to higher costs for both buyers and sellers. In addition, agents need to rely on advanced trading strategies in order to maximise profit (or minimise costs). For example, prosumers with an inefficient energy forecasting strategy may unintentionally set a too high sell price, resulting in an unmatched order for their energy. Since there is no buyer at the time when they produce and inject the energy into the grid, prosumers make zero profit, unless they invest in batteries that can store the untraded energy. Those agents can then inject the energy at the time they find a buyer. Lastly, separate energy balancing mechanisms need to be employed [41] to cope with real-time demand response.

More recent publications also using multi-agent environments to simulate energy trading markets and strategies con be found in [47] and [48], In the first paper, Sesetti et al. brings an intelligent agent based energy market management system to incorporate energy storage systems into onsite energy trading markets. The paper also proposes bidding strategies for energy storage systems to participate in onsite-energy markets. The efficacy of the proposed market management system is proved using a distribution system with two microgrids simulated on OpenDSS (comprehensive electrical power system simulation tool primarly for electric utility power distribution systems). In the second paper, Luo et al. propose a system that includes two layers. In the first layer, a multi-agent system is designed to support the prosumer network, and an agent coalition mechanism is proposed to enable the prosumers to form coalitions and negotiate electricity trading. In the second layer, a Blockchain based transaction settlement mechanism is proposed to enable the trusted and secure settlement of electricity trading transactions formed in the first layer. Compared with existing research on distributed energy trading, the proposed system decouples the upper-level trading negotiation process among prosumers from the autonomous, local energy management of individual prosumers. This structure is flexible and can therefore adapt to prosumers with different types and heterogeneous energy resources.

Previous references were individual agents with individual strategies participating in local energy markets. In [49] the participation is through a Virtual Power Plant (VPP). A VPP is an aggregator of distribute energy resources, storage facilities, and loads into a single flexible entity, and this paper is proposed a Fuzzy Optimization (FO) to optimize the day-ahead bidding strategy. The main advantage of FO is that it does not increase the problem size significantly as the number of uncertain parameters increases. The test results demonstrate the effectiveness of FO in increasing the realized profits. The results also show that, by using the fuzzy model to include uncertainty, the VPP is able to enhance the operation plan of the conventional generator by reducing its operating time.

An important contribution under this thesis has been to consider a different trading mechanism approach, which is to consider incentive mechanisms instead of support policies such as net metering and feed-in tariff. In [50] it is proposed the NRG-X-Change, a novel mechanism for trading of locally produced renewable energy that does not rely on an energy market or matching of orders ahead of time. This mechanism uses a new decentralized digital currency for energy exchange, called NRGcoin [51]. All payments by consumers and to producers are carried out in NRGcoins, instead of fiat money. The currency can then be exchanged on an independent open market for its monetary equivalent, e.g. Euro, Dollar, Pound, etc. This mechanism is based on a blockchain technology and it is also implemented under a multi-agent environment.

Even in market-based mechanisms an EPM is needed: independently from injection and withdrawal of energy, NRGcoins are traded on an open currency exchange market for their monetary equivalent. Agents use an EPM based on RF technique to determine the quantity to trade and the adaptive attitude bidding strategy to determine the bid/ask price [51].

Electric Power System Optimization

In an uncertain and complex environment, to ensure secure and stable operations of large scale power systems is one of the biggest challenges that power engineers have to address today. Actually, power system engineering has the longest history of development among the various areas of electrical engineering [52]. Several optimization issues have been considered in power system planning such as optimal power flow, maintenance scheduling, economic dispatch, production scheduling, etc.

Traditionally, power system planning optimization and decision-making are based on mathematical model where the main objective is to minimize undesirable things (e.g. cost, energy loss, errors, etc.) or maximize desirable things (e.g. profit, quality, efficiency, etc.), subject to some constraints. Some of the most important traditional mathematical optimization techniques used in power systems problems have been: linear and quadratic programing [53][54], nonlinear programing [55] and dynamic programing [56]. However, there are many uncertainties in power system problems because they are large, complex, and geographically widely distributed. It is desirable that solution of power system problems should be optimum globally, but solution searched by mathematical optimization is normally optimum locally. These facts make it difficult to deal effectively with many power system problems through strict mathematical formulation alone.

AI algorithms, which promise a global optimum or nearly, have been proved to significantly improve current system planning optimization problems. These methods are being constantly improved and developed to deal with large size systems and ever more interconnected systems. Optimization problems are complex due to a large number of constraints, therefore, finding better solutions with short computational time is the goal of these methods.

Bibliography on the fuzzy set theory applications in power systems has been presented in [57]. It shows that fuzzy set theory has been applied mainly in voltage and reactive power control, load forecasting, fault diagnosis, power system protection/relaying, stability, and power system control, etc. More recent publications on fuzzy theory power systems optimizations can be found at [58][59].

Laghari et al. [60] have presented a bibliographical survey of ANN and their applications to power systems. ANN has been mainly used in following areas of power systems: i) Planning (long term load forecasting – section 2.3, capacitor placement/voltage control [61]-[64]) ii) operation (short-term load forecasting – section 2.3, fault diagnosis [65][66], load flow [67], static and dynamic security assessment [68][69], hydro scheduling, transient stability [70]-[72]) iii) analysis (power system stabilizer [73]-[75]).

A survey of Expert Systems (ES) applications in power system is presented in [80], and shows that ES have been applied to various areas of power systems, including: power system planning, alarm processing, fault diagnosis, power system protection, power system restoration and reactive power/voltage control. More recent applications of ES in power plants can be found at [76].

Genetic Algorithms (GA) have been receiving increasing amounts of attention due to their versatile optimization capabilities for both continuous and discrete optimization problems. Two interesting examples have been selected as power system optimization: A recent survey of power system optimization with a special chapter for Evolutionary Algorithm (EA) and GA [54], while in [79] a concrete application of GA is used to optimize the total cost while simultaneously minimize the power loss and maximize the voltage profile.

2.1.3 Integration of renewable energy resources

With the increase penetration of renewable energy to the grid the key technical potential challenges that effects quality of power observed includes: voltage fluctuation, power system transient and harmonics, reactive power, electromagnetic interference, switching actions, synchronization, long transmission lines, low power factor, storage system, load management, and forecasting and scheduling [81]-[83].

These problems mostly occurred for wind and solar energy due to the uncertainties associated to weather conditions. Biomass, hydro and geothermal energy sources are more predictable and they have no significant problem on integration with the smart grid [81]. Any device to be connected to the electric grid has to fulfil standardized power quality requirements [84]. To ensure adequate power quality in the grid it is a prime concern today to mitigate these problems and Government, industries and researchers are working together for a sustainable efficient smart power grid. Depending on the challenge it can be addressed through hardware components or through computational models (most of them based on SC and ML algorithms).

Voltage fluctuation, reactive power compensation, harmonic distorsion and energy storage, although in some uses cases they may rely on AI technologies, they are usually approach through power electronics in batteries, substations, transformation centres and power lines.

Synchronisation of grid frequency, voltage, and phase is a promising research challenge to control power quality. The most popular grid synchronisation method is based on phase-locked loop. Other techniques for synchronization include detecting the zero crossing of the grid voltages or using combinations of filters coupled with a non-linear transformation [82]. More recent studies use SC techniques such as FL grid synchronization with similar results [85].

2.1.4 Renewable Energy Generation Forecasting

Renewable energy generation forecasting has seen major advancements in its research and in the application of AI approaches over the last years. It is now a key component to the integration of large penetration of wind and solar power for many players in the energy system. Improvements in the forecast provide substantial economic and reliability benefits. With the high penetration of solar, and wind power, the scheduling and operation of power systems are faced with the challenges of increasing uncertainty that sometimes can be handled by applications and algorithms based on AI. In renewable energy forecasting, recent developments include coupled systems that combine observations, Numerical Weather Prediction (NWP) [86] and AI models, to improve accuracy. The AI techniques often include EA [87], ANN [88][89], combination of FL and ANN [90], Kalman Filters [91][92] and self-organized maps[93]. In general, coupled methods often lead to more accurate forecasting than raw NWP forecast. The usage of these advanced techniques for forecasting has become much more acceptable and widespread in recent years.

DL methods have been also increasingly applied to renewable generation prediction. Since DL has the characteristics of flexibility, self-adaptive learning abilities, and the relaxation of the need of physical and phenomenological assumptions, it is expected that prediction accuracy can be enhanced by combining DL methods with more data sources. An example in the last years has been the research on predicting wind ramps. Paper [94] uses a Multi-Layer Perceptron Neural Network (MLP-NN) for wind forecasts, using a NWP model as input. Paper [95] proposes a long short-term memory based wind power prediction model, which is advanced and practical in the field of wind power prediction. Principal Component Analysis (PCA) is used to choose input samples and reduce the dimensions of the input variables of the long short-term memory prediction model based on NWP data. Simulation results show that, compared with backpropagation neural network and SVM model, the proposed prediction model has higher prediction accuracy and greater potential for engineering applications.

Uncertainty in renewable forecasting is usually handled from two different perspectives. On the one hand, with ensemble and probabilistic forecasting methods. The forecasts can be generated by running a variety of NWP models, running a single NWP with various model configurations, or a combination thereof. The main advantages of ensemble methods are their ability to better characterize the most likely power production, represent potential extreme scenarios, and provide a way to quantify the uncertainty [96][97]. They can also be coupled with aforementioned statistical models and ground-based observations to obtain power production estimates. The result is any number of power production forecast scenarios that can be blended to produce a “best guess” deterministic forecast based on the ensemble. Each of the ensemble members can be evaluated individually or collectively as well, to assess extreme scenarios, establish confidence intervals, or define probability distribution functions that describe the likelihood of different scenarios. Nevertheless, assemble approach can be very computationally intensive.

On the other hand, a more efficient approach is to identify analog conditions with a single deterministic forecast and use those to form an analog ensemble [98]. It is a three-stage process that is executed independently at every target site for every hour of the reconstructed period. First, the analog predictors are selected beforehand based on their known or anticipated correlations to the predictand. Second, other historical cases with conditions similar to those in the target window are identified (known as analogs) by looking at a time window centred around the same hour of the day for every day in the training period, and ranked by closeness of match. Third, the *k* best analogs are selected, and the corresponding observed values of the predictand are retrieved. The latter constitute the ensemble members for hour *t*. This technique shows promise for improving upon deterministic forecasts while providing reliable forecast uncertainty information.

2.1.5 Image recognition technology and its application in power system security management

Image recognition has become in the last five years a well-used technology for DSOs, TSOs and other assets owners, in their daily works. It helps in multiple tasks related to power system security management; wind turbine inspections, facility plant health, substation maintenance and inspection, lines and pole inspections, to name a few.

Currently the fault diagnosis of blades is mainly dependent on manual visual inspections, which consumes plenty manpower and may not detect the damage in time. In [99], image-based damage recognition of wind turbine blades is proposed. The process of damage recognition is realized by two-stage learning. The first learning stage is deep feature extractor. A deep convolutional neural network (ConvNet) is built to emulate the behaviour of the visual cortex to extract deep features of the blade images. The second learning stage is pattern learning. Deep features of the training blade images are extracted used to train a classifier to identify the damage type of the blades. The damage identification of the wind blades can be realized by the combination of the deep feature extractor and the classifier. The proposed method has the highest accuracy, which even reach to 100%.

Another application for wind turbines can be found in [100]. Wang et al. proposes the use of image colour analysis for fire detection in wind turbines. They propose a flame recognition Learning Vector Quantization neural network model, based on the colour of flame characteristics, flame area change, centroid mobility characteristics and circularity of the flame.

Image recognition has been used to read SM consumptions. In [101] Kanagarathinam et al. uses text detection and recognition of seven segment numerals from collected SMs display samples. The algorithm outlines a 7-step process consisting of four types of operations-object detection, noise removal, image segmentation and numeral recognition based on pixel density feature extraction and adds a maximally stable extremal regions algorithm pre-processing to overcome the challenges in text detection and text recognition in camera captured images. The proposed method of text detection and recognition algorithm attains better accuracy compared to existing methods. Implementation of optical character recognition may help to bring automation in energy management process.

Image recognition has been used for power substation maintenance as well since many years ago. For instance, in 2004, in [102] the system implemented is able to conduct automatically intruder detection, fire alarm zone detection and substation meter reading. It can be used to prevent theft as well. Moreover, the proposed system is also very useful for short-term and ad hoc power substation monitoring because the system requires neither spare contact nor additional transducer.

A more recent application (2018) in substations can be found in [103]. Knowing the state of the disconnect switches in a power distribution substation is important to avoid accidents, damaged equipment, and service interruptions. This information is usually provided by human operators, who can commit errors because of the cluttered environment, bad weather or lighting conditions, or lack of attention. In this paper, Nassu et al. introduce an approach for determining the state of each switch in a substation, based on images captured by regular pan-tilt-zoom surveillance cameras. The proposed approach includes noise reduction, image registration using phase correlation, and classification using a Convolutional Neural Network (CNN) and a SVM fed with gradient-based descriptors. By combining information given in an initial labelling stage with image processing techniques to reduce variations in viewpoint, the approach proposed achieved 100% accuracy on experiments performed at a real substation over multiple days.

Detection of power lines is by far the most researched topic. It is applied to improve maintenance and inspections of electricity cables in the distribution system. A good state of the art until 2014 of computer vision for the management of power transmission lines can be found in [104]. In a more recent article [105], Xia et al. propose an image recognition and processing model that is mainly based on DL. It uses a CNN and a RNN, which are able to generate a corresponding sentence in plain English to describe the content of the image on electric equipment inspection. Meanwhile, extra information obtained from the image is submitted to image semantic comprehension subsystem, thereby helping electric utilities to automatically decide and perform next phase of work.

In all these studies is crucial the collection of enough sample images of electrical inspections, which is nowadays limited because they are not open access but owned by the utilities.

2.2 Energy Modelling

The aforementioned AI applications have in common that they will mostly rely in energy models. An energy model is a computer based model of an energy system or component, for instance, the production of a power station or a prosumer, the consumption load profiles of an entire building or an appliance, or the behaviour of an entire electricity distribution system. Models may be limited in scope to the electricity sector or they may attempt to cover an energy system in its entirety.

Energy models are mainly used for simulation, which allows us to save resources and time. It allows also to take into account most of the variables that play an important role, such as the consumption, weather, people, utility rates and so on. Energy modelling enables to represent, analyse, make predictions, and provide insight into real systems. In the case of a dwelling, for instance, it helps us to choose between different designs and materials. By adjusting variables, we can check their impact on the energy requirement. There are many different energy models and applications:

Backcasting Models

To construct visions of various desired future outcomes for an energy system based on a backward approach, identifying policies and programs that will connect that specified future to the present [106]. This type of modelling undertakes the challenge of discussing the future from the direction opposite to that of the forecasting models.

Scenario Analysis Models

To explore the future pathways for an energy system based on a comparison between a limited number of desired future scenarios with a reference scenario (i.e., a baseline). The intervention scenarios provide projections for a wide range of the factors which drive the energy scenario. These include production, consumption, trade, prices, investments, technology mixes, and many others [107].

Supply-Side Models

Mostly focused on energy supply technologies, with a particular perspective on renewable energy systems, fossil-based power plants, oil and gas industries, etc. They are characterized by a limited spatial scale and generally consider a single piece of technology using a simulation technique or experimental work to perform the analysis, including the design and performance of the system [108][109]. The models may, therefore, be characterized as calculating supply-side parameters related to technology design or, in some cases, the operation of such technologies. Models involving optimization techniques have been proposed to predict the functional relationship between system performance and the critical system parameters through the estimation of the optimal design of supply technologies [110].

Integrated Models

These models look at the full set of processes within an energy system [111]. Integrated models of energy systems can present a complete perspective to achieve overall reductions in energy consumption and are better at analysing the direct and indirect effects of policies. In this category, agent-based simulation models are widely used [112]. These models are especially designed to investigate the reliability of energy generation and supply networks in energy systems by a greater reliance on aggregate accounting and rule-based approaches than the behavioural profiles of consumers [113][114]. In these models, the agents are characterized by bounded rationality and can learn, adapt, and reproduce. Other models include assessment models which represent studies of the entire economy and how local and global policy decisions might shape energy performance [115]. It is possible to test the impact of various scenarios by decomposing trends in energy consumption and generation into socioeconomic, technological, and demographic developments.

Demand-Side Models

These consist of a broad range of methodologies which focus on determining the final energy consumption in the entire economy or a particular sector, such as the buildings (residential, industrial, and commercial), industrial energy use, and the transportation system. The overall methodological focus of this cluster of energy system models is to consider the demand side endogenously, and the supply-side issues are not considered at all. These models mostly rely on bottom-up simulation techniques to estimate energy demand. The applications and data used for this thesis are focused on this typology of energy models, in concrete electricity load or demand models. In the next sections of this chapter, we investigate about different AI techniques for electricity load forecasting, with special focus in FIR.

Despite the diversity of practices among the models, many of the challenges they face are common to them all. Some of them can be addressed as the complexity of the modelling techniques and data availability or resolution.

2.3 Electricity Load/Demand Forecasting

Electricity load forecasting has been an important research area since many decades ago. First papers dates back to 1960 [116], where regression analysis was applied and its research popularity and field applications has never stopped growing. Nowadays, load forecasting has become an essential element for the correct operation of electric utilities and the rest of actors in the energy sector and have an established interest in forecast accuracy. Forecasts are required for proper scheduling activities, such as generation scheduling, fuel purchasing scheduling, maintenance scheduling, investment scheduling, and for security analysis.

Electricity load forecasting is typically divided in short, medium and long term. The long-term plan evaluates how well the short-term planning commitments fit into long-term needs. No commitment needs to be made to the elements in a long-term plan, and capacity and location are more important than timing in long-term forecast. In other words, it is more important to know what will eventually be needed than to know exactly when it will be needed [117]. Each category is equally important in the energy sector for the correct operation of the power system.

Short-term Load Forecast (SLF)

We consider a SLF when time-scale lasts for few minutes, hours to one-day ahead or a week. SLF aims at economic dispatch and optimal generator unit commitment, while addressing real-time control and security assessment.

In this thesis we are focusing in the short-term prediction; hourly prediction of the next 24 hours. In the next section we analyse how AI and more concretely SC and ML are used to this end.

Mid-term Load Forecast (MLF) and Long-term Load Forecast (LLF)

MLF is considered when the time period is from one month to a year. MLF aims at maintenance scheduling, coordination of load dispatch and price settlement so that demand and generation is balanced. On the other hand, the time-period of LLF is from few years (> 1 year) to 10-20 years ahead. LLF aims at system expansion planning, i.e. generation, transmission and distribution. In some cases, it also affects the purchase of new generating units. MLF and LLF have special impact in the system maintaining plan and design, therefore, they have a strong economic impact correlation; utilities do not want a huge investment going in vain.

MLF and LLF is much less popular than SLF and it requires a different approach. Learning and estimation for LLF and MLF are hard tasks due to lack of training data and increase of accumulated errors in long period estimation. Makridakis et al. [118] suggested that these forecasts should be based on (i) identifying and extrapolating mega-trends going back in time as far as necessary; (ii) analogy and (iii) constructing scenarios to consider future possibilities. The influence of economic factors on load in long-term horizon becomes only visible on longer time scales or in extreme situations such as economic crisis of 2008.

First AI models for MLF and LLF are dated early 90's. The use of FL with linear regression, ANN and Bayesian theory for MLF and LLF are reported in references [119][120][121]. The use of ANN in a hybrid manner with fuzzy and regression methods to give more flexible relations between load and load impacting variables can be found in [122]. ANN is widely accepted for MLF and LLF and with the increasing importance in the last years of DL it is the most used methodology. In [123] a model was developed using Radial Basis Function (RBF) Neural Network. Results indicate that the forecasting model based on this approach has a high accuracy and stability. In [124] Baek et al. describes a mid-term daily peak load forecasting method using recurrent ANN. The results of case studies using load data of South Korea are presented to show performances and effectiveness of the proposed methodology. A very recent publication [125] described and applied a methodology that provides a LLF for European countries using ANN. The results are benchmarked against the results of the current temperature-dependent polynomial regression functions approach that is currently being used in the mid-term adequacy forecast by European Network of Transmission System Operators (entso-e). Results shows a mean absolute percentage error of 2.8% for the proposed ANN model, whereas the common approach as used by entso-e shows an average error of 4.8%.

Support vector regression is the most common application form of SVM and its use in load forecasting is reported in literature [122]-[130]. Other recent SVM examples can be also found in [131][132].

Recently, emerging heuristic optimization algorithms have been applied to optimize the design and effectiveness of AI-based predictors/forecasters and have been reported in literatures. Examples are Genetic Algorithms (GA) [133]-[135], Expert System (ES) [136]-[139], and EA [140].

2.3.1 Short-term electricity load forecasting

The integration of SG capabilities in today's power systems, together with the increasing penetration of renewable energy sources becomes the process for robust and accurate load forecasting more complex, calling for more effective techniques in order to fulfil excellent operation of the power system and planning management. Moreover, due to nonlinearity and nonstationary features of electric loads, which are affected by weather conditions, socioeconomic factors, seasonal and random effects, electric load signals are characterized by high unpredictability, making the electric load forecasting a very arduous challenge.

For SLF, the electric load is highly connected with meteorological factors such as temperature, humidity, wind speed and specially typology of day. The change in holidays, weekdays, weekends, the day before and after holidays also has impacts on the load forecast [141]. The analytical methods work well under normal daily circumstances, but they can't give contenting results while dealing with meteorological, sociological or economical changes, hence they are not updated depending on time. On the contrary, AI techniques have indicated the capability of learning complex nonlinear relationships, which are difficult to model, and accordingly making them popular [141].

The literature on SLF is much more extensive than that on MLF and LLF. This is also reflected by the literature reviews that have been published over the last forty decades. It is not our intention to perform an intensive literature review on AI techniques for SLF but to give an overview about the different techniques and approaches used, where the contributions in this thesis are located.

In the SLF literature, there are some State-of-the-Art (SoA) reviews of AI load forecasting approaches classification and comparison. An impressive review was performed in 2016 by Hong and Fan [142] that offers a detailed revision of most important SLF literature over the last forty years divided by conceptual and empirical studies. Moreover, the article includes an analysis of most notable techniques (ANN, FL, SVM, Gradient Boosting), methodologies and evaluation methods, and common misunderstandings. Another SoA empirical review of three AI techniques; ANN, SVM and Adaptive Neuro-Fuzzy Inference System (ANFIS) is performed by Zor et al. in [143]. Studies investigated in the context of this paper show that these three AI techniques have the potential for excellent forecasting. Another conceptual SoA review is performed by Singh et al. in [144], where they classify demand forecasting techniques in i) traditional mathematical techniques such as Regression, Multiple Regression, Exponential Smoothing, etc.; ii) Modified Traditional techniques such as Adaptive Demand Forecasting, AR, ARMA and ARIMA models, SVM; and iii) SC techniques such as GA, ANN, FL and Knowledge-Based Expert Systems.

In addition to the previous reviews, there are also conceptual and empirical individual studies, for each of the aforementioned techniques. Some of the most popular and recent literature classified by SC techniques are:

SC Technique	***No. of reference***	***Contributions / Challenges to Face***
FL	[145]-[148]	Application of fuzzy regression to SLF, and provided several tips for fuzzy regression based forecasting. Interval type-2 for load forecasting.
ANN	[149]-[153]	The accuracy of ANN based forecast model is dependent on number of parameters such as forecast model architecture, input combination, activation functions and training algorithm of the network and other exogenous variables affecting on forecast model inputs.
SVM	[154]-[158]	By the regularization parameter, user can avoid overfitting. Expert knowledge about the problem can be built by kernel trick. Defined by a convex optimization problem (no local minima) and there are efficient methods to solve it.
Gradient Boosting	[159]-[161]	The models allowed the electricity demand to change with the time of-year, day-of-week and time-of-day, and also on public holidays, with

		the main predictors being current and past temperatures, and past demand.
DL and RL	[162]-[173]	To improve prediction accuracy based on big datasets from Advance Metering Infrastructure (AMI) and weather forecast systems.

Since 2010 with the increase in computational power, SC hybrid techniques have gain popularity. They are proposed with the combination of two or more algorithms either to combine strengths or to overcome the deficient parts of the techniques. They can be used for instance to find optimal set of fuzzy rules, for feature selection of most important variables to be used in a forecasting model or to improve the training capability of a neural network. Popular hybrid methods for SLF in the literature include adaptive neuro-fuzzy inference system (ANFIS) or GA combined with ANN and FL. A summary of this two hybrid approaches with good reputation in the literature are:

Hybrid Technique	***No. of Papers***	***Contributions / Challenges to Face***
ANFIS	[174]-[176]	Combination of a RBF network to forecast the load on the prediction day with no account of the factor of electricity price with the ANFIS system to adjust the results of load forecasting. This system integration improves forecasting accuracy and overcome the defects of the RBF network. FL is used to modify the load curves on selected similar days and to utilize fuzzy inference with similar day approach where fuzzy parameters have been optimized and these adaptive fuzzy parameters helps in improving the quality of forecasted results. Combination of ANN for the primary forecasting of the load over the next 24 hours. In the second step, a wavelet transform, the similar-hour method and ANFIS are used to improve the results of primary load forecasting.
ANN / FL – GA	[177]-[179]	Fuzzy-ANN combined with a chaos search GA and Simulated Annealing to exploit the advantages of the two methods and, furthermore, to eliminate the known drawback of the traditional ANN trained by the backpropagation method. Artificial Immune System (AIS) that imitates the immunological ideas to train networks. The proposed AIS algorithm hardly requires 6 iterations & 21 data sets to converge to the same extent than GA & Particle Swarm Optimization (PSO) (150 iterations & 36 data sets). Integrated GA and ANN to estimate and predict electricity demand using stochastic procedures. The curves for demand estimation using GA and actual data show a good fitness while the relative error of GA method is significantly smaller compared to regression methods.

Fuzzy Inductive Reasoning for SLF

SLF has been dealt with many different methodologies and techniques, however, under this Ph.D. thesis we have proposed a new approach for SLF based on a hybrid technique called Fuzzy Inductive Reasoning (FIR), which combines an entropy-based feature selection process with FL. This is the first time FIR has been used for these applications.

The conceptualization of the FIR methodology arises out of the General System Problem Solving approach proposed by Klir [180]. This methodology of modelling and simulation has the ability to describe systems that cannot be easily described by classical mathematics or statistics, i.e. systems for which the underlying physical laws are not well- understood. A FIR model is a qualitative non-parametric model based on fuzzy logic. The FIR model consists of its structure (relevant variables or selected features) and a pattern rule base (a set of input/output relations or history behaviour) that are defined as if-then rules. The whole process of FIR is explained in [181].

The FIR methodology is, therefore, a modelling and simulation tool that is able to infer the model of the system under study very quickly and is a good option for real time forecasting. On the other hand, some of its weaknesses are that as long as the depth and complexity increase the computational cost increases too, and also the parameters to choose during the fuzzification phase, which can be mitigated using EA to tune the parameters [182]. In addition, FIR it is not able to perform predictions when it contains missing data in the input pattern and also it discards pattern rules with MVs.

FIR was used for SLF applications and compared for the first time with other SC techniques in this Ph.D. thesis [183]. We compared the prediction accuracy in 35 random test days (24-hour forecasting) between evolutionary SVM, AR-Net, RF and FIR. The results showed that accuracy, on average, was better in FIR. Thus a first conclusion from this study was that i) FIR could be comparable in terms of accuracy against other popular techniques such as ANN and RF. A second conclusion was that ii) it was promising methodologies for the task of predicting electric load and, therefore, should be studied more deeply. Afterwards, in [141] we wanted to investigate more and to understand how the model's accuracy is affected by FSP parameters. To do so, we studied the prediction errors versus the number of most important variables and depth. We also added and additional model comparison with ARIMA, which helped to compare them with a traditional time series forecasting statistic technique. We proposed hybrid methodologies that combines feature selection based on entropies with SC and ML approaches (FIR, RF and ANN). The results based on this study, show on average that FIR is the methodology that performs a better forecast followed by the RF and the NN.

Flexible FIR: increasing robustness and accuracy

An accurate SLF technique can alleviate operating costs, keep energy markets efficient, and provide a better understanding of the dynamics of the monitored system. On the contrary, an erroneous prediction might cause either a load overestimation, which leads to the excess of supply and reserve and consequently more costs and contract curtailments for market participants, or a load underestimation resulting in failures in gathering adequate provisions, hence more expensive complementary services.

There are few studies about how MVs affect the model generation and prediction in SC techniques but, to the best of our knowledge, not in FIR. Most of them focus in reconstructing MVs but not how the model deals with MVs in online training.

While FIR displays high prediction accuracy in complex systems, it has several limitations when missing data are present in the forecasting process. We observed that robustness and accuracy of Standard FIR decreased significantly when the input data in Standard FIR contained consecutive MVs or high number behaviour matrix’s rules with MVs, because they were automatically discard. To cope with this situation, as part of this Ph.D. research we proposed a new version of the FIR fuzzy forecasting, which was called Flexible FIR prediction [184]. The research on this new version of FIR continued in [185]. In this journal the performance of Flexible FIR is compared against Standard FIR for different SLF building profiles, with significant results: Flexible FIR was able to predict electricity consumptions accurately, making use of partial information, whereas Standard FIR cannot. With 70% of MVs in the training data Flexible FIR was able to predict almost 100% of testing data (while Standard FIR failed in all test days), while decreasing just 10% the accuracy compared to a scenario with only 10% of MVs.

Model parametrization is also critical from SLF accuracy point of view and becomes a bottleneck in the value-chain. Model parametrization in FIR has led to an important number of publications [183]-[186] where we have pointed out for instance the implications of the depth's mask and complexity's mask in prediction accuracy. Another example is the selection of the *k* Nearest Neighbours (kNN) in the fuzzy forecasting process. The FIR inference engine is based on the kNN approach, commonly used in the pattern recognition field. The forecast of the output variable is obtained by means of composition of the potential conclusion, which results from firing the kNN rules whose antecedents have best matching with the actual state. Smaller *k* brings higher noise sensitivity, whilst larger *k* causes smoother decision boundaries and lower noise sensitivity [187]. To overcome these issues, in some methods, *k* is tuned in order to find the optimal mapping function, but it is a time-consuming process [188].

In [189], we perform an analysis of the impact that kNN has in FIR prediction and we present an updated version of Flexible FIR that uses a K nearest neighbour Optimal Selection (KOS) algorithm during the FIR prediction phase. To this end, SLF of different public buildings is performed to compare accuracy of Flexible FIR with and without the updated version of the KOS algorithm implemented. It has been proved that, on average, the forecasting accuracy of Flexible FIR combined with KOS improves. Our algorithm helped to decide in each hourly prediction, which is the optimal number of neighbours to compute the next output state in Standard and Flexible FIR. Most of the parametrization approaches in the literature are performed from an offline perspective and take considerable computational time and resources. Therefore, it is important to highlight that this process is performed online, without significant computational time in the forecasting process, in comparison with GA or other EA with tremendous computational cost.

The outcomes of our studies in Flexible FIR sheds light on robust SC methodologies for smart home, smart buildings and smart grid applications.

Chapter 3: Conclusions and Future Research

There is a new paradigm in how we produce, transport, distribute and consume the energy; more sustainable, from a local level and with new technologies that allow end-users to actively participate in the energy markets. The smart grid is the evolution of the standard electricity grid that is allowing this transformation and artificial intelligence a key strategy for mastering some of the greatest challenges of the smart grid. A new generation of algorithms and applications arises from the use of artificial intelligence that unlocks new features, which are translated in many benefits for the society. Typical areas of application are energy modelling, electricity trading and planning, demand side management, integration of renewable energy resources or image recognition for operation and maintenance tasks.

What most of this application areas have in common is that they rely on models and predictions of energy systems at some point of the value-chain. Energy forecasting, and in particular, short-term load forecasting, is key for the use of artificial intelligence in the energy system and should enable these applications. For example, for proper planning activities, such as generation planning, fuel purchasing planning, maintenance planning, investment planning; for demand side management, such as demand response programs; for energy trading, especially at local level, where productions and consumptions are more stochastics and dynamic; better forecasts also increase grid stability and thus supply security. Primarily in the field of forecasts, artificial intelligence can help facilitate and speed up the integration of renewables because they heavily depend on weather conditions and therefore a proper forecasting give us a unique position to simulate and anticipate scenarios.

Inaccuracy or failure in the short-term load forecasting process may be translated not just in a non-optimal solution but also in frustration of end-users, especially in new services and functionalities that empower citizens. For example, in energy trading by prosumers, if trading mechanisms do not offer an optimal solution of energy exchange, it may end-up in a non-profitable investment in solar panels, batteries and so on. Therefore, energy forecasting models based on artificial intelligence must be robust and reliable.

Short-term load forecasting has been of great interest in the last two decades, there has been an exponential number of publications from 2000 to 2016 and more moderate from 2017 to 2020, most of them are focused in machine learning and soft computing techniques with high reputation in the energy and artificial intelligence domain, mainly represented by artificial neural networks. In the last decade, hybrid approaches with fuzzy-logic, deep learning or genetic algorithms have gain huge popularity and, based on the results from the literature research, it can be concluded that hybrid models combining artificial intelligence techniques are a clear step forward to improve reliability and achieve higher accuracies in predictions.

With these premises, in this thesis we wanted to know how FIR, a hybrid soft computing technique that has been proved to be a powerful approach for model identification and system's prediction over dynamic and complex processes in different real world domains, would perform in a domain not studied so far: energy. The results showed that FIR has been able to model and predict energy dynamic systems with an accuracy and time performance as good as other popular machine learning and soft computing techniques. In addition, FIR logic and its inferred knowledge is easier to understand than of other soft computing techniques such as artificial neural networks. This is a remarkable feature because the patterns and the causality relations obtained by FIR models can be studied and understood by energy experts.

Having said that, some weaknesses and potential improvements in FIR have been identified and addressed under this thesis. As previously stated reliability, robustness and accuracy in short-term load forecasting are critical for the good use of the predictions generated. Due to some limitations in Standard FIR, it is not able to perform predictions when it contains missing data in the input pattern and, also, it discards pattern rules with MVs (Missing Values). To cope with this situation, a new version of FIR has been design, implemented and tested with real world data. This new version called Flexible FIR is able to cope with missing information in the input values, as well as learn from instances with MVs in the behaviour matrix, without compromising significantly the accuracy of the predictions. Moreover, Flexible FIR comes with new forecasting strategies that can cope better with loss of causality of a variable and dispersion of output classes than classical *k* nearest neighbours, making the FIR forecasting process more reliable and robust.

Furthermore, Flexible FIR addresses another major challenge in the modelling with soft computing techniques, which is to select best model parameters. One of the most important parameters in FIR is the number *k* of nearest neighbours to be used in the forecast process. The FIR inference engine is based on the *k* nearest neighbours' approach, commonly used in the pattern recognition field. The predicton of the output variable is obtained by means of a composition of the potential conclusions, which results from firing the *k* nearest neighbours rules whose antecedents have best matching with the actual state. The challenge to select the optimal *k*, dynamically, is addressed through an algorithm, called KOS (K nearest neighbour Optimal Selection), which has been developed and tested also with real world data. It computes a membership aggregation function of all the neighbours with respect their belonging to the output classes. While with KOS the optimal parameter *k* is found online, with other approaches such as genetic algorithms or reinforcement learning is not, which increases the computational time.

These improvements make Flexible FIR fit very well into scenarios of Edge Computing (EC) where streaming edge analytics, must be reliable, robust and small enough to fit and run on an IoT gateway or an even smaller device, next to or even on the actual machine. Also when there is not consistent connectivity and is not possible to make use of cloud computing, for instance to tune model's parameters. Following this idea, the concept of a Second Generation Smart Meter based on EC has been proposed under this thesis, which integrates Flexible FIR as energy prediction module running on the edge and an EC agent with capabilities for trading locally produced renewable energy with a novel mechanism called NRG-X-Change that uses a new decentralized digital currency for energy exchange, called NRGcoin.

To sum up, the aim of the work developed in this dissertation was to introduce FIR as a solid alternative to other popular machine learning and soft computing approaches and how it had to be improved to fit better in some applications for the energy sector.

3.1 Summary of results obtained

The results obtained in this doctoral thesis address several of the problems that are characteristic of energy dynamic systems. In a first step, an analysis of the feasibility of FIR methodology for modelling and prediction of next 24 hours electricity load was developed. The FIR methodology offers a model-based approach to predict either univariate or multi-variate time series. A FIR model is a qualitative, nonparametric, shallow model based on fuzzy logic. In order to demonstrate the scalability of the models in different profiles of usage, three functional zones of the Universitat Politècnica de Catalunya (UPC) were used in the experiments. They all had different profiles of usage and locations, thus, affecting different climatology, consumption patterns, schedules and working days. The results obtained in this work indicated that FIR is a good alternative to other well-reputed techniques such as random forest, auto-regressive neural network and evolutionary supported vector machines. On the other hand, FIR allowed to determine the more relevant features, reducing considerably system's complexity.

The data from the different UPC buildings were used again to perform a deeper study in FIR Feature Selection Process (FSP). One of the aims of these experiments were to understand how the model's accuracy was affected by the insertion of new input variables. The designed experiments were divided into two stages: 1) a FSP based on Entropy, used in all the artificial intelligence methodologies selected in the study plus ARIMA, which helped to compare them with a traditional time series forecasting statistic technique, and 2) a FIR, random forest, artificial neural networks or ARIMA model training process. In the FSP stage, three depths were studied: 24 hours, 48 hours and 72 hours. In the model training stage, different sets of input variables and complexities were also studied. In general, artificial intelligence methodologies adapted better to consumption changes when they perform the predictions, following the real shape of the curve, detecting better the peaks and achieving very low prediction errors. With regards to ARIMA, it is a more conservative methodology, which does not produce high errors but the accuracy was far from FIR.

In these experiments we also concluded that the prediction errors of all the methodologies decrease considerably when the variable *is working day* was added to the set of input variables. On average, the optimal depth of the mask was 48 (24 hour past consumption plus 24 hour consumption of the previous week) for all buildings and methodologies. The more depth, the more visibility and better results. Finally, as for the computational cost, with the configurations used, all methodologies are fast to obtain the model (less than 10 sec. for a training set of a year hourly data) and to perform a prediction. On the contrary, the FSP increases exponentially with the depth and number of past values selected, therefore it is important not to select masks with high complexity if we want to do it online. The evaluation criteria used in these experiments were the normalized mean squared error (NMSE) and the mean absolute percentage error (MAPE).

Secondly, a new version of FIR called Flexible FIR that is able to cope with the problem of MVs in the input pattern, as well as learn from instances with MVs in the behaviour matrix was developed.

FIR is able to deal with MVs as it has been already proved in a large number of applications. However, its capacity to deal with it decreases significantly when the complexity of the mask is big, because it implies the generation of a big number of pattern rules in the behaviour matrix containing MVs. To put in context, for a qualitative data matrix of 358 registers containing 24 consecutive MVs, and a mask depth of 168, it is possible to generate up to 191 pattern rules that contain at least one missing element. This can become a huge problem due to the fact that the standard prediction process of FIR methodology discards the pattern rules containing MVs, and, therefore, the valid pattern rule base available is reduced significantly. This implies that the FIR prediction process is barely able to predict a new input pattern due to the fact that not similar behaviour exists in the behaviour matrix. In addition, input patterns containing a MV are also discarded. Therefore, the question is: is it possible not to lose all the information from the pattern rules generated containing a MV? Can we increase the robustness of FIR, so it does not crash in these situation? Which would be the impact in the forecasting accuracy? As it has been explained in previous chapters, robustness and reliability in energy applications is a must, therefore, we need to guarantee reliable prediction values.

For this experiment, data from three different UPC buildings, with different typologies, were selected and from the 8760 consumption registers of each building for one year, we incorporated randomly MVs in 10% of the data. Different model configurations (complexity, depth and input variables) were also tested.

We obtained promising results because, on average, prediction errors of Standard FIR and Flexible FIR were equivalent and sometimes the accuracy was even higher with Flexible FIR. Moreover, while Standard FIR, in some configurations, could only predict 82% of the instances, Flexible FIR predicted 100%. This confirmed that robustness of the improved methodology. We also certified that Flexible FIR accuracy increases when the input variables and depth increases. The evaluation criteria used in these experiments were the NMSE and the MAPE.

A third round of experiments were performed with two goals: i) to study the impact in terms of prediction accuracy and the number of values predicted, when MVs in the training dataset were increased progressively; and ii) the development of new forecasting strategies for Flexible FIR that minimizes the dispersion of output classes due to MVs.

Electricity load consumptions from 8 different buildings of the UPC were obtained for this study, in order to have a training/test sample with high diversity of consumptions. They have different profiles of usage (sports centre, library, administration building, restaurant, etc.), belong to five different campuses and are located in different cities. Thus, affecting different climatology (temperature, humidity, solar radiation, etc.), consumption patterns, schedules and working days. Similarly than in the second round of experiments, the data did not contain MVs because we needed the real consumptions to evaluate Standard and Flexible FIR. Instead, MVs were added artificially.

Here the question was: is there a Flexible FIR strategy able to provide significant better online electricity load forecasting in presence of MVs? To answer this question, we compare the results of Standard FIR and 8 Flexible FIR strategies. The comparison was carried out through two experiments with different objectives; in the first experiment the aim was to understand how possible it was to perform predictions with partial information in the input pattern and how it is correlated with the number of input variables and depth of the mask in each strategy. The second experiment consisted on increasing the number of MVs in data progressively and to evaluate the accuracy of the predictions, in each strategy as well. As in the previous experiments, with different FSP configurations.

With this data, once again, the optimal configurations of Standard and Flexible FIR were found when mask depth was 48 and the number of input variables 6. However, from 10% of MVs in data the variable hour of the day was not contributing to improve prediction accuracy.

In the first experiment, a comparison between the 8 new Flexible FIR forecasting strategies developed was performed. The results suggested that the use of causal relevance in the output forecast calculation, mitigates the impact of dispersion of output classes and the loss of causality, due to removing partial information from the behaviour matrix. Computational cost in strategies with causal relevance based on the Mean Squared Error of a validation dataset was higher than strategies based on the quality of the mask, because in the first case the whole FIR forecasting process was needed. Thus, we believe that for edge computing applications where computational cost is an important variable to consider, strategies with causal relevance based on the quality of the mask are the best option to be implemented.

In the second experiment, the robustness of Flexible FIR and its eight strategies were demonstrated, taking into account that the percentage of registers predicted was around 96% when the percentage of MVs in the training dataset was around 73%. A significant decrease in the number of registers predicted was observed when MVs were present in 82% of the training dataset, a scenario which is difficult to imagine. Furthermore, the difference of prediction error when the percentage of MVs in the training dataset was 9% (sMAPE = 13.86%) and 63% (sMAPE = 24.87%) was around 11%, which is not a big difference taking into account the volume of information lost. Thus, Flexible FIR is able to keep a good compromise between information lost and prediction accuracy.

This time, the evaluation criteria used was the symmetric mean absolute percentage error (sMAPE) unlike the previous experiments. The reason behind this decision was that MAPE puts a heavier penalty in negative errors than in positive errors. In some applications it is interesting to penalize negative errors, because higher predictions than actual values can lead to an extra purchase of assets. In our study, we were only interested in the forecasting accuracy, thus, to penalize equally negative and positive errors.

A fourth round of experiments was considered to answer the following question: how could we improve some of the parameters selection of FIR and Flexible FIR in an online process, without compromising computation cost and time. As we pointed out in previous chapters, a different approach could be done from an offline perspective and with optimal search algorithms, however, we wanted to investigate an approach that could fit under edge computing applications with limited resources and with computation from the edge.

In FIR and Flexible FIR, the new output state values can be computed as a weighted sum of the output states of the previously observed *k* nearest neighbours. In previous studies and applications about FIR, the new output state is typically computed using five nearest neighbour. It has been always considered, based on the results, that five nearest neighbours were a good compromise between dispersion and accuracy. However, this assumption is far from an optimal solution. How would we optimally choose the number of *k* nearest neighbours in Standard or Flexible FIR models, if we are aware that this number affects to the forecasting accuracy? Would we choose a random *k*? Would we run *n* different models with different *k* values and choose *k* based on the best result?

We developed a methodology called KOS that was tested and validated with one-year electricity consumptions of three UPC buildings. The buildings included were: 1) one administrative building in ETSEIAT faculty in Terrassa; 2) the Library of EPSEVG faculty in Vilanova; 3) Building C6 with different classrooms at FIB faculty in Barcelona. The energy consumptions of these 3 buildings were collected through a remote metering system every hour. Therefore, there were 24 recordings per day and per location over one year, which means 26.280 hourly consumptions used in the experiments.

The aim of the experiments was to evaluate if KOS was able to perform, on average, as good as the number of nearest neighbours that performed better, and to understand the implications of the parameter *k* in FIR and Flexible FIR. To do so, it was performed three different experiments: i) with *k* from 1 to 15 neighbours, ii) with the new KOS and iii) with a random value of *k*. The results for the individual buildings showed that the performance with KOS was practically the same or better than the number of nearest neighbours that performed better and on average, the configuration with the best results was when the KOS was used. In addition, KOS was always performing better than when *k* has a value of 5. The evaluation criteria used in these experiments was the sMAPE.

Summarizing, the major contributions of this doctoral thesis are the following:

- A survey of Artificial Intelligence techniques that have been applied in Smart Grid applications and in Short-term Load Forecasting.
- An analysis of the feasibility of FIR methodology for modelling and prediction of multiple electricity consumptions profiles.
- An improved and more robust version of FIR called Flexible FIR, which is composed of:
    - An algorithm that makes the inference process flexible in a dynamic way;
    - An algorithm that can deal with input values containing MVs;
    - 7 new FIR forecasting strategies to cope with dispersion of output classes.
- An algorithm to optimally and dynamically select the number of nearest neighbours to be used during the FIR or Flexible FIR forecasting process.
- A new generation of Smart Meters based on edge computing with:
    - Flexible FIR as energy prediction module running on the edge;

- An edge computing agent with capabilities for trading locally produced renewable energy with a novel mechanism called NRG-X-Change with a new decentralized digital currency for energy exchange, called NRGcoin.

We can conclude that for modelling and predicting energy dynamic systems, Flexible FIR is certainly an improvement on its predecessor, Standard FIR, in terms of prediction accuracy, robustness and parameters selection. We also would like to emphasise that the models presented are applicable to any problem in which deterministic and stochastic variables are considered.

3.2 Future research

During this thesis we first tried to address the main objectives stated in the thesis proposal. But the research, as it happens in life, evolves and changes; new challenges arises and some objectives considered to be important at the beginning of this journey are today less important. Leonardo da Vinci said *Art is never finished, only abandoned*, art teaches us that we are never done learning, never done exploring, never done growing. The same happens in science and in this research, with every experiment carried out, new ideas raised and potential future works.

It is form this unfinished work and from some of the initial objectives not prioritize in the thesis that we can build-up the future research.

The first think that should be performed in the near future is to validate more extensively the algorithms developed in this dissertation. As explained before, all of them were proved with data from UPC buildings. It is necessary to go step further and apply these algorithms other consumption profiles, for instance, data coming from private dwellings. That would demonstrate the scalability also in housing sector, which are the most important beneficiaries of the predictions. And despite that, the models presented are applicable to any problem in which deterministic and stochastic variables are considered, it would be necessary to study Flexible FIR and the algorithms developed under this thesis in other domains.

Another important future work would be to validate FIR, Flexible FIR and the algorithms developed for short-term electricity production. The main reason why this was not included in the experiments is because we did not have production data neither from public or private buildings. In case that we had, based on the literature review, we believe that predictions would heavily rely in weather forecasting (solar radiation, wind speed and cloud cover). Thus, with reliable weather forecasting data, our thought is that the accuracy would be high.

Although most Advanced Metering Infrastructure provides data from end-users in hourly basis, there are some providing higher granularities from 15 minutes or less. We believe it would have great value to evaluate Flexible FIR performance with these granularities and study if it could be translated in quality improvement of predicted values. To study the implications of higher granularities could shed light in the compromise between prediction quality and data storage. Moreover, increase in granularity could also have positive implications in local energy trading, thus it should also be studied.

From the fuzzy methodology point of view, and taking into account that forecasting accuracy can drop due to the presence of uncertainty in the operation of energy systems or unexpected behaviour of exogenous variables, we would like to study the application of Interval Type-2 Fuzzy Logic Systems in the context of FIR methodology. Type-2 fuzzy logic approaches allow additional degrees of freedom, being an excellent tool for handling any kind of uncertainties and, therefore, more likely approximate short-term load forecasting in a better way. On the other hand, this kind of approaches are more computationally expensive, being his issue a problem for its application in edge computing scenarios. We think that an interesting future research would be the design and implementation of a Type-2 Flexible FIR approach to study its performance compared with current Flexible FIR that is based on Type-1 fuzzy sets.

A first proof of concept of the Next Generation of Smart Meters (NGSMs) has been implemented, however, the Energy Prediction Module (EPM) used is far from being an optimal solution. We propose as a future work to use Flexible FIR for the EPM, i.e. to implement Flexible FIR in a raspberry PI and validate effectiveness of negotiations. Random forest has been already applied in this hardware. Flexible FIR performance has been demonstrated for different consumption profiles and can cope with missing information in the input values, as well as during the prediction phase. Moreover, it works well in an “isolated” approach like in edge computing scenarios. It does not rely on deep learning or high computational cost plus it has been demonstrated to seemly choose autonomously some FIR input parameters.

Chapter 4: Bibliography and References

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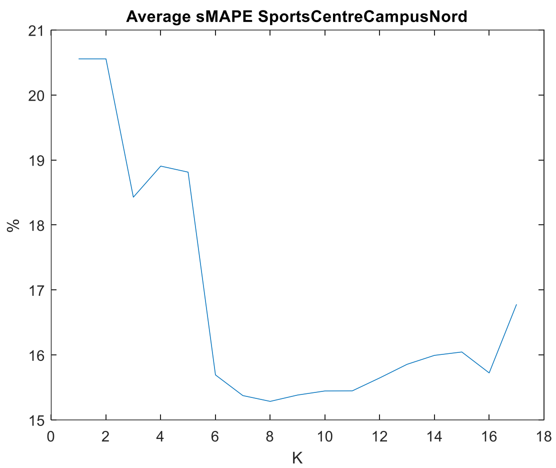
Appendix I: Results of KOS algorithm when applied to all buildings data

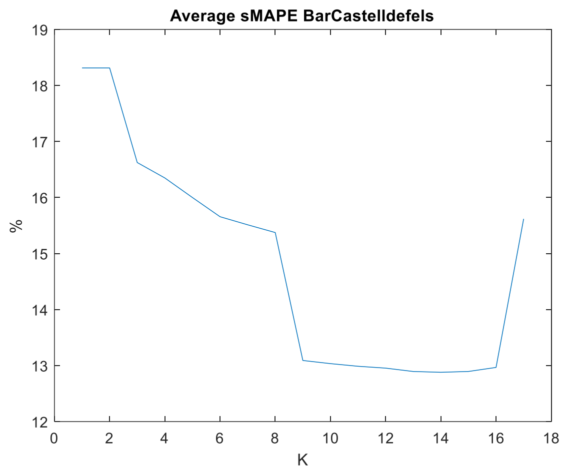
The following figures show the error evolution computed with sMAPE in different Flexible FIR configurations for the seven buildings of the UPC: Sports Centre Campus Nord, Bar Castelldefels, Bilblioteca Terrassa, Biblioteca Vilanova, Edifici Campus Terrassa, Building C6 Barcelona, Biblioteca Manresa.

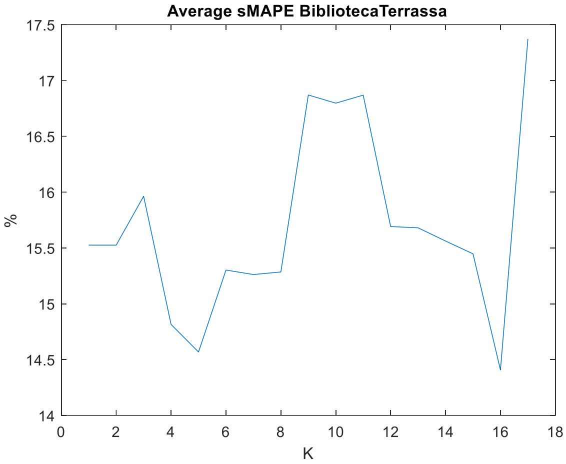
The percentage for each *k* is an average of the error prediction in the 35 test days considering the seven buildings of study. The values of *k*, from 1 to 15 are the results of Flexible FIR when the output forecast computation uses *k* nearest neighbours. *k* equal to 16 represents the experiment with the new KOS in each prediction, while *k* equal to 17 represents the result with a random *k* in each prediction.

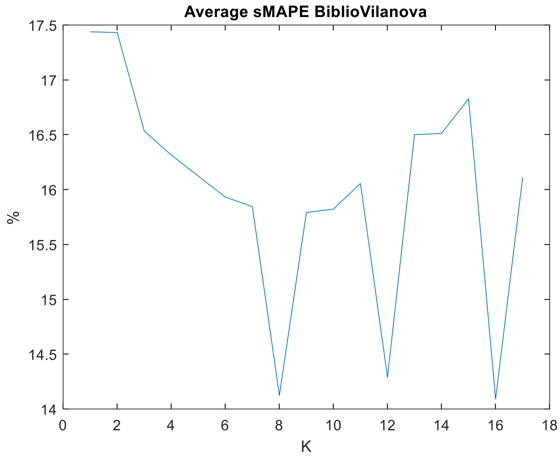
On the one hand, the results obtain in some buildings, i.e. Sports Centre Campus Nord, Edifici Campus Terrassa and Building C6 Barcelona, show that the performance of KOS is slightly worse than the best number (*k*) of neighbours. On the other hand, the results obtained in Bar Castelldefels, Bilblioteca Terrassa, Biblioteca Vilanova and Biblioteca Manresa, show that the performance with KOS is slightly better than the optimal number of neighbours.

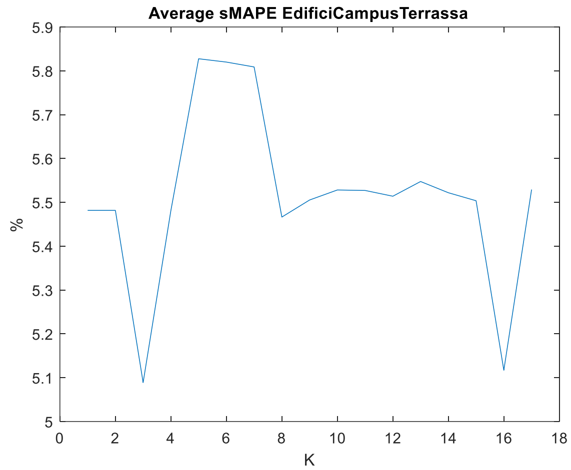
It is shown that, on average, the forecasting accuracy of Flexible FIR combined with KOS improves. Our algorithm helps to decide in each hourly prediction, which is the optimal number of neighbours to compute the next output state in Standard and Flexible FIR.

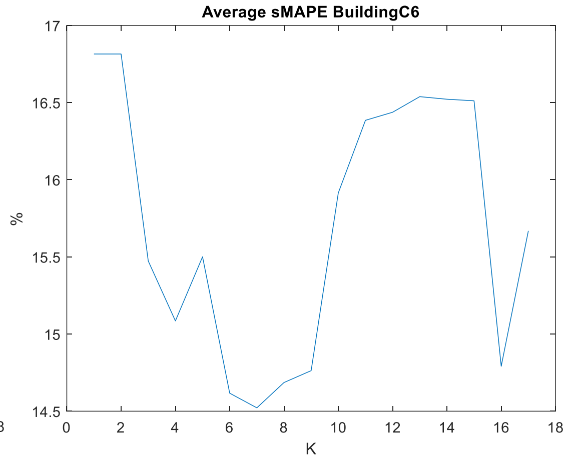


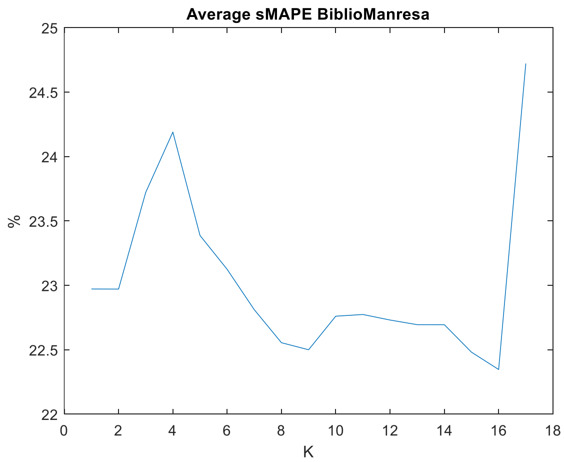



Average sMAPE BibliotecaTerrassa
17.5
17
16.5
16
15.5
15
14.5
14
%
0 2 4 6 8 10 12 14 16 18
K


Average sMAPE BiblioVilanova
17.5
17
16.5
16
15.5
15
14.5
14
%
0 2 4 6 8 10 12 14 16 18
K


Average sMAPE EdificiCampusTerrassa
5.9
5.8
5.7
5.6
5.5
5.4
5.3
5.2
5.1
5
%
0 2 4 6 8 10 12 14 16 18
K


Average sMAPE BuildingC6
17
16.5
16
15.5
15
14.5
%
0 2 4 6 8 10 12 14 16 18
K


Average sMAPE BiblioManresa
25
24.5
24
23.5
23
22.5
22
%
0 2 4 6 8 10 12 14 16 18
K