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# *CONTRIBUTIONS TO THE ENERGY MANAGEMENT OF INDUSTRIAL REFRIGERATION SYSTEMS: A DATA-DRIVEN PERSPECTIVE*

Tesi doctoral presentada per a l'obtenció del títol de Doctor per la Universitat Politècnica de Catalunya, dins el Programa de Doctorat en Enginyeria Electrònica

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*data de lectura de la tesi*

*“There are two ways to live your life.*

*One is as though nothing is a miracle.*

*The other is as though everything is a miracle.”*

*For example, …*

*“Look deep into nature,*

*and then you will understand everything better.”*

*But nevertheless what is certain is that...*

*“Not everything that counts can be counted,*

*and not everything that can be counted counts.”*

*ALBERT EINSTEIN (1879-1955)*

## Abstract

Nowadays, energy management has gained attention due to the constant increment of energy consumption in industry and the pollution problems that this fact supposes. On this subject, one of the main industrial sectors, the food and beverage, attributes a great percentage of its energy expenditure to the refrigeration systems. Such systems are highly affected by operation conditions and are commonly composed by different machines that are continually interacting. These particularities difficult the successful application of efficient energy management methodologies requiring further research efforts in order to improve the current approaches.

In this regard, with the current framework of the Industry 4.0, the manufacturing industry is moving towards a complete digitalization of its process information. Is in this context, where the promising capabilities of the data-driven techniques can be applied to energy management. Such technology can push forward the energy management to new horizons, since these techniques take advantage of the common data acquired in the refrigeration systems for its inner operation to develop new methodologies able to reach higher efficiencies.

Accordingly, this thesis focuses its attention on the research of novel energy management methodologies applied to refrigeration systems by means of data-driven strategies. To address this broad topic and with the aim to improve the efficiency of the industrial refrigeration systems, the current thesis considers three main aspects of any energy management methodology: the system performance assessment, the machinery operation improvement and the load management.

Therefore, this thesis presents a novel methodology for each one of the three main aspects considered. The proposed methodologies should contemplate the necessary robustness and reliability to be applicable in real refrigeration systems. The experimental results obtained from the validation tests performed in the industrial refrigeration system, show the significant improvement capabilities in regard to the energy efficiency. Each one of the proposed methodologies present a promising result and can be employed individually or as a whole, composing a great basis for a data-driven based energy management framework.

**Keywords**: *artificial intelligence, compressors, cooling capacity, data-driven, energy management, load disaggregation, load management, machine learning, neural networks, non-intrusive load monitoring, outlier detection, partial load ratio, performance assessment, refrigeration systems, self-organizing maps, uncertainty.*

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practice during the entire life all the gained and received knowledge during this path. Thank you very much to everybody.

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## Acronyms and their definitions

| | | | |
|---|---|---|---|
| **ANN** | Artificial Neural Network | **NN** | Neural Network |
| **BMU** | Best Matching Unit | **OCSVM** | One-Class Support Vector Machine |
| **BP** | Back Propagation | **PCM** | Phase Change Material |
| **CBC** | COIN-OR branch and cut | **TES** | Thermal Energy Storage |
| **COP** | Coefficient of performance | **TRNSYS** | Transient Systems Simulation Program |
| **DDBB** | Data Base | **PDF** | Probability Density Function |
| **ETP** | Equivalent Thermal Parameter | **PID** | Proportional-Integral-Derivative controller |
| **IMSE** | Integraded Mean Squared Error | **PLC** | Programmable Logic Controller |
| **IoT** | Internet of Things | **PLR** | Partial Load Ratio |
| **LDA** | Linear Discriminant Analysis | **PuLP** | Linear Programming Toolkit for Python |
| **MAE** | Mean Absolute Error | **ReLU** | Rectified Linear Unit |
| **MAPE** | Mean Absolute Percentage Error | **RUL** | Remaining Useful Life |
| **MLP** | Multi-Layer Perceptron | **SCADA** | Supervisory Control and Data Acquisition |
| **MU** | Matching Unit | **SOM** | Self-Organizing Map |
| **MPC** | Model Predictive Control | **SGD** | Stochastic Gradient Descent |
| **MSE** | Mean Squared Error | **TES** | Thermal Energy Storage |
| **MVKDE** | Multivariate Kernel Density Estimation | **TRNSYS** | Transient Systems Simulation Program |
| **NILM** | Non-Intrusive Load Monitoring | **U-matrix** | Unified distance matrix |

## Nomenclature, symbols and abbreviations

| | | | |
|---|---|---|---|
| $\mathbf{B_{COP}}$ | Benchmark COP, near-optimal COP | $\boldsymbol{Qerror}$ | Quantization error |
| $\mathbf{BP_{COP}}$ | Best Proliferated COP | $\boldsymbol{Q'}$ | Estimated disaggregation NN structure output. |
| **C** | Compressor | **S** | Space to refrigerate |
| **DA** | Discretized Area | $\mathbf{S_{COP}}$ | Ideal COP without consider affecting variables |
| $\boldsymbol{dp}$ | Discharge pressure [bar] | $\boldsymbol{SNN}$ | Sub-net of the disaggregation structure |
| $\boldsymbol{E_{SOM}}$ | SOM error function | $\boldsymbol{sp}$ | Suction pressure [bar] |
| $\boldsymbol{G}$ | Number of active evaporators | $\boldsymbol{spSP}$ | Suction pressure set point [bar] |
| $\mathbf{H_{COP}}$ | Best Historical COP | $\boldsymbol{T}$ | Temperature [ºC] |
| $\boldsymbol{L}$ | Number of active evaporators lower bound | $\mathbf{D_{COP}}$ | Dataset COP |
| $\boldsymbol{M}$ | Multiplication layer of the disaggregation structure | $\boldsymbol{Th}$ | Threshold |
| $\boldsymbol{Nhf_{wn}}$ | Neighbourhood function | $\boldsymbol{TSP}$ | Temperate Set Point [ºC] |
| $\boldsymbol{P}(\mathbf{X})$ | PDF of x | $\boldsymbol{U}$ | Number of active evaporators upper bound |
| $\boldsymbol{P}_{\mathbf{h}}(\mathbf{x})$ | PDF of x with specific bandwidth h. | $\boldsymbol{W}$ | Electrical work or power [kW] |
| $\boldsymbol{Q}$ | Cooling capacity [kW] | $\boldsymbol{w}$ | Neuron weight vector |
| $\boldsymbol{Q_{in}}$ | Heat absorbed by the refrigerant [J] | $\boldsymbol{\beta}$ | Summation of neuron distances |
| $\boldsymbol{Q_{out}}$ | Heat rejected by the refrigerant [J] | $\boldsymbol{\Delta T}$ | Temperature change |

| | | | |
|---|---|---|---|
| $\boldsymbol{\varepsilon_p}$ | Suction pressure error [%] | $\boldsymbol{\tau}$ | Timesteps since an evaporator was turned ON |
| $\boldsymbol{\varepsilon_T}$ | Temperature error [ºC] | $\boldsymbol{\varphi}$ | Timesteps since an evaporator was turned OFF |
| $\boldsymbol{\rho}$ | Compressors above 90% of PLR [%] | | |

NOTE: Further details of the nomenclature and symbols of the thesis equations are explained in the equation description of the respective chapter.

# 1.

## Introduction

This chapter contains the foundations on which this thesis research is engaged. The research topic, problem, hypothesis and objectives are detailed as well as a brief description of the case study and a summary of the subsequent chapters.

CONTENTS:

# 1 Introduction

## 1.1 Research topic

Energy is determinant for the economic competitiveness and growth, and its demand is increasing year over year [1]. Moreover, the energy consumption has been a recurrent topic for more than two decades due to the connection with the global warming and climate change issues [2][3][4]. As a result of this constant increase of energy demand, arise the necessity to develop energy management strategies.

> *"The objective of the energy management is to minimize the energy expenditure without affecting the product output while minimizing environmental effects [1]."*

Particularly, the industry sector consumes nearly one third of total global energy supply and 36% of energy-related $CO_2$ emissions [5]. In this regard, industry has developed initiatives aligned with the framework of Industry 4.0 or the Smart manufacturing to improve decisions for optimizing diverse processes and reduce the energy consumption [6][7]. These aforementioned paradigms include topics such as the minimization of the energy and material usage, maximize the environmental sustainability, improve the safety or the economic competitiveness [8].

To implement this smart manufacturing concept and to tackle all the aforesaid topics from a data-driven point of view, the data from all the processes has to be collected, stored, cleaned and analysed. In order to perform such tasks, emerging technologies as IoT, wireless sensor networks, big data or cloud computing are used [9].

This energy awareness in industry, combined with this smart manufacturing approach where all the data from the processes is acquired, bring the opportunity to develop new data-driven energy management methodologies. The topic of this thesis is the development of a data-driven energy management framework, applied to an industrial refrigeration system for improving its operation in regard to an energy efficiency objective.

> *"Data-driven energy management is a set of processes, based on data, that enable an industry or organization to implement actions in order to diminish the energy consumption and become more efficient."*

Commonly, data-driven energy management strategies are composed of three main parts: the energy data standards, the performance measurements and the analysis and optimization of energy consumption [10]. The first part, which defines the standards of how the data has to be acquired and stored, corresponds to an engineering problem which is being solved by many industry standards, for this reason is out of the scope of the thesis. Therefore, the presented thesis focuses on how to robustly measure the performance of the process, and how to optimize such procedure from a data-driven perspective.

On the one hand, the performance measurements are developed to measure the operation efficiency and quantify the potential improvement of a process. Generally, the performance evaluation is done comparing the desired process against a “standard” or “optimal” operation of that specific process [11]. However, that standard operation is highly influenced by the current status of the process. In this regard, data-driven strategies are useful for such purposes as can infer the current operation and use it together with historical records to build a more robust and reliable “standard” operation model that can be employed to compare and evaluate the performance under changing operation conditions [12].

On the other hand, the optimization of the energy consumption, is focused on developing different measures to apply in the studied processes to reduce the energy expenditure. To tackle such optimization or improvement issue, in literature, three main approaches are presented independently of the process to optimize [13]: the energy efficiency, the demand response and the energy storage.

The energy efficiency concept refers to using less energy to produce the same amount of useful output[14], indeed, to configure the industrial process in a specific manner in order to reduce the energetic utilization. Otherwise, the demand response consists in altering the energy consumption patterns in order to smooth the demand or to avoid peak periods [15]. The two aforementioned optimization measures can be faced by data-driven techniques suggesting the optimal set points found in the historical database for a concrete operation condition. Contrary, the energy storage focuses on designing process equipment in order to minimize energy usage during peak consumptions. This setup is outside of the scope of the current thesis, since the aim of the thesis is to manage current process resources in an optimal way using the acquired data, rather than adding or modifying current process equipment.

The huge increment of stored data in industrial processes with the rapid development of the smart factory framework, provide a perfect scenario to push forward the data-driven methodologies in manufacturing environments. Furthermore, the constantly increase of energy usage, the scarcity of natural resources along with the pollution emissions raise, induce the necessity to apply these emerging data-driven tools to the energy management field.

### 1.1.1 Case study: vapour compression overfeed refrigeration system

The industrial nature of the proposed thesis imply that the developed methodologies must be validated in a real industrial process. In this regard, the contributions of the thesis are focused on generating an energy management framework for an industrial refrigeration system. This section includes the description of the refrigeration system object of the thesis, in which the proposed methodologies have been validated. Although the research has been focused on this specific industrial system and its particularities, it is possible to adapt the methodologies presented in other industrial processes taking into account its peculiarities. Even though the above-mentioned adaptability potential, is out of the scope of the study to readjust the methodologies to each industrial system particularities.

In order to enhance the comprehension of the thesis structure and objectives, it is required to identify the features, main components and operation principles of a vapour compression refrigeration system. The **Fig 1.1.1** depicts a basic vapour compression refrigeration cycle, with the elemental components: the compressor, the condenser, the expansion valve and the evaporator.

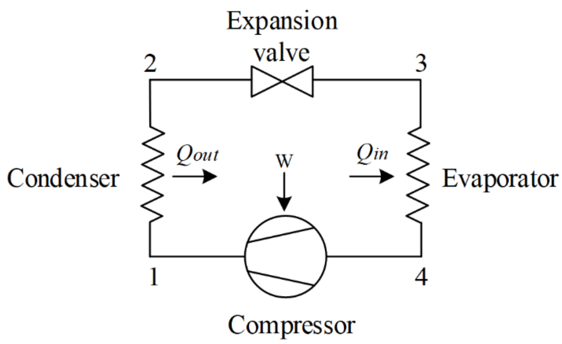


**Fig 1.1.1 - Basic vapour compression refrigeration cycle.**

The goal of these systems is to remove heat of a space, basically they remove heat from a cold reservoir ($Q_{in}$) to a hot one ($Q_{out}$). To carry out this task, the refrigerant which is a fluid with specific thermodynamic properties, circulates through the system illustrated in **Fig 1.1.1** in order to absorb and reject heat. The principles of operation are the following: at (4), the refrigerant is in low pressure vapour state and it is compressed, by supplying work ($W$) using the compressor, to a high pressure vapour state (1). Afterwards, in the condenser, the vapour is cooled to its saturation to obtain the refrigerant in liquid state in (2), in this step is where the heat is rejected. Once the refrigerant is in a high pressure liquid state, in the expansion valve, the pressure is lowered to the initial value (3). And, finally, the refrigerant is vaporized in the evaporator, where the heat of the space is absorbed, and the cycle restarts (4) [16].

Although the basic vapour compression cycle includes the main principles of refrigeration, in large industrial facilities, where various evaporators and low temperatures are required, are commonly employed overfeed refrigeration systems, **Fig 1.1.2**. These systems are based on the same principles as the vapour compression cycle explained below but incorporate some particularities. The major difference is that the overfeed systems are composed of two circuits with its own mass flow, joined in a low pressure receiver used as a liquid-vapour separator. In the first circuit, the compressor suctions the saturated vapour from the low pressure receiver to maintain the desired pressure in the receiver. As in the basic cycle, the vapour is cooled in the condenser and the liquid is stored in the receiver. The receiver storage the refrigerant in high pressure liquid state and provides liquid to the low pressure receiver through the expansion valve when its necessary. In the second circuit, this low pressure receiver supplies saturated liquid refrigerant, by means of a pump, to the distributed evaporators, overfeeding the evaporators and obtaining an efficient heat transfer. Finally, the refrigerant returns to the low pressure receiver in a mixed vapour-liquid state as it is only partially evaporated in the evaporator [17].

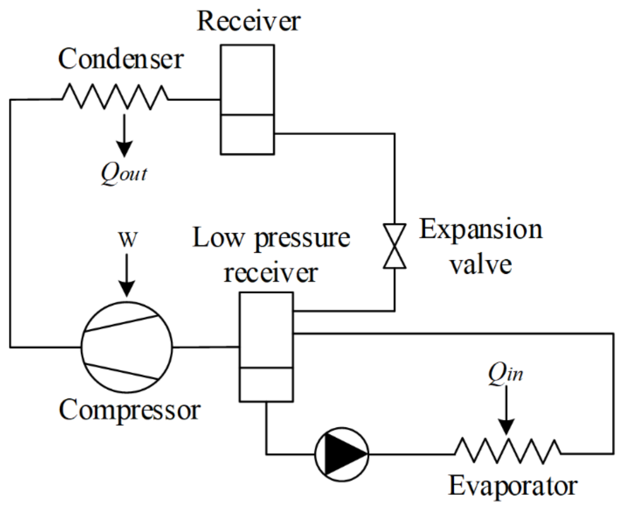


**Fig 1.1.2 - Overfeed vapour compression refrigeration cycle.**

The main concern about these systems is the power consumption in order to remove the heat. Typically, the efforts to reduce this energy consumption are focused on the compressor, the part that consumes the majority of the electrical energy and considered the main part of the system [18]. Such overfeed systems, in real industrial facilities, are composed of various compressors, condensers and evaporators in parallel allowing different configurations to remove the desired heat. In this capability to manage the configurations of the system lies opportunity to improve the efficiency. In the refrigeration system studied, various screw compressors in parallel are used to cover the cooling demand. This screw compressors employ slide valves to regulate the cooling capacity, the measure of the system ability to remove heat. One of the main particularities of these type of compressors is the low cooling capacity when the slide valve is below the nominal operation conditions, **Fig 1.1.3** [19].

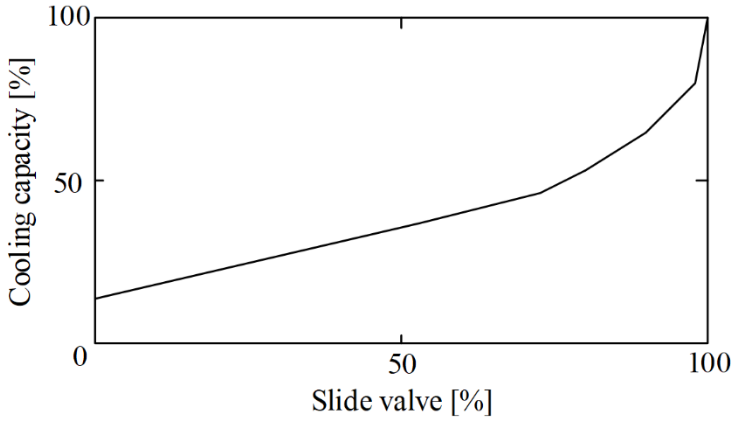


**Fig 1.1.3 - Theoretical curve of the cooling capacity versus the slide valve of a typical screw compressor.**

Therefore, due to the nature of these systems and the load changes, the majority of the time, the compressors are operating in underload conditions [20], which provokes their operation out of their nominal design values. Moreover, the refrigeration systems are also influenced by various variables of the process which have to be considered and the cooling load of the desired space to refrigerate [21]. Further information regarding the system description, the subset of variables registered in the database and their register information is given in the Annex I of this thesis.

Hence, in this thesis, a data-driven energy management methodology is proposed taking into account all the available information in the system and the natural constraints that affects the system performance. To face energy management and to characterize the framework of the thesis, three main concerns arise: (i) the capability to measure the system performance under different operation conditions, (ii) the optimal set point recommendation of the compressors to diminish the energy expenditure and (iii) the management of the load to avoid inefficient compressors operation. All the methodologies suggested in each of the mentioned parts of the framework are detailed in the subsequent chapters and also implemented in the real refrigeration system described.

## 1.2 Research problem

This section explores the state of the art limitations in the development of data-driven energy management strategies for the optimization of industrial refrigeration systems. In this regard, a critical requirement in any energy management system, is that the methodology proposed needs to be able to measure and verify the benefits of the energy efficiency actions. ISO 50001 provides the guidelines to accomplish such goal, where the first step starts with the energy monitoring, a necessary tool to provide awareness of the current consumption and the effectiveness of the proposed actions [22]. Regardless of the importance of this initial step, assessing the energy efficiency in an industrial environment is difficult due to multiple factors that affect the performance of a process [23].

Therefore, complex industrial systems need to be addressed in a holistic point of view, taking into account all aforementioned factors. The adoption of these external factors that affect energy efficiency is a challenging task that need to be incorporated to the current energy performance strategies in order to obtain a reliable efficiency metric. Additionally, this data-driven era, boosted by the smart industry paradigm, permits the creation of trustworthy efficiency evaluation metrics based on historical operation conditions of the systems and avoiding the ideal physical and simulation based approaches [24]. These classical approaches correspond to the physical modelling strategies that consist in finding the coefficients of the physical equations that lead the behaviour of the process, techniques that have been proved to be complex in industrial processes [25]. However, the strategies grounded on data also present some concerns regarding the validity of the data acquired or the capability to deal with new data not seen before [26]. Consequently, there is still room for research in the energy performance evaluation topic from a data-driven perspective:

> *"Obtaining a robust and reliable energy performance evaluation is an essential milestone towards the* ***energy efficiency****. Such evaluation may consider all the factors that affect the performance, as well as the capability to deal with new or abnormal system conditions in order to provide a realistic assessment."*

In regard to the reduction of the industrial processes overall energy consumption, various approaches are suggested in literature. On the one hand, an increase of the efficiency can be achieved by means of technical and set point management of the industrial systems. Again, data-driven approaches take advantage of the data acquired from the industry to improve and guide the processes to reduce its energy consumption. However, taking into consideration these data-driven approaches, some limitations appear regarding the inability to extrapolate the historical operation to modes that the system has never used before. The data-driven techniques are limited, in order to be reliable, to the variable space defined by the data with they were built [27][28]. Another drawback is the computation time of the optimisation strategies, which needs a more detailed attention and even more in industrial environments which are highly dynamic [29].

> *"Offering a trustworthy set point recommendation is an imperative requirement in energy industrial systems, especially in data-driven techniques. This recommendation system should take into account the systems variability, the quickness of response and the set point recommendation reliability."*

Furthermore, the demand response of the industrial processes can be improved in order to reduce the energy consumption by different approaches. In this regard, the most common approaches in literature deal with load shifting techniques [30]. To be able to apply such techniques, it is necessary to be aware of the consumption of each load in the industrial system. Hence, a modelling or monitoring task is required in order to identify the loads behaviour [31]. The issue, is that it is non-viable to monitor all the industrial energy loads due to its elevated cost and it requires the use of NILM techniques. The lack of industrial appliances datasets to train the NILM models, the elevated number of equipment in the industrial systems, and its simultaneity of operation, are problems that the state of the art is currently addressing [32]. Otherwise load shifting strategies are mainly based on forecasted load responses which are highly related to unpredictable or uncertain factors [33].

> *"In order to develop a data-driven load shifting technique is crucial to know the equipment consumption and to avoid load assumptions that can affect the management. Thus, the load response strategy must consider the load simultaneity issue in order to disaggregate the consumption, the high number of machines in an industrial environment and the capability to abstract the decisions from the uncertain forecasts."*

In essence, several problems and limitations are being addressed in the current state of the art and further research is required to develop a reliable energy management methodology able to deal with the aforementioned issues. The proposed contributions to this lacks in literature have to overcome the presented drawbacks and have to fulfil the performance improvement potential to enhance the energy efficiency.

## 1.3 Hypotheses

Considering the identified problems mentioned above about the research topic, the following hypotheses have been formulated as starting point for this research thesis:

- With the usage of data-driven techniques and machine learning algorithms, a framework able to improve the efficiency of a refrigeration energy system can be developed.
- The data-driven energy management framework can be performed tackling the different key aspects separately: the performance assessment, the operation improvement and the load management.
- The performance benchmark of a refrigeration system can be improved, in terms of assessment reliability, if the different operation conditions and the various machines involved in the system are considered.
- The integration of an uncertainty management strategy in the performance benchmark will improve the assessment robustness when dealing with abnormal operation data.
- The bias of the data-driven models associated with historical data can be mitigated generating new artificial samples. Thus, a broader casuistry can be considered by the same model.
- A data-driven set point recommendation methodology will be able to manage the refrigeration system compressors in a near-optimal manner.
- The utilization of a trend classification model will allow the reduction of harmful and unnecessary switching actions of the compressors.
- Employing a novel semisupervised neural network, will be possible to estimate the individual cooling loads of the system with high accuracy, taking advantage of the refrigeration system consumption.
- With the individual load information, it is possible to balance the cooling demand to attain a more efficient and smoothed consumption requirements.

In conclusion,

- The contributions to data-driven energy management methodologies shall allow to overcome some of the current state of the art limitations towards a better energy efficiency in industries.

## 1.4 Aim and objectives

Considering the aforementioned problems and hypothesis, the aim of this thesis is the proposal of a data-driven energy management framework for industrial refrigeration systems. Such framework shall propose a methodology for each one of these important aspects of the system: the performance assessment, the set point recommendation and the load management. The final aim of the framework is the increase of the overall refrigeration system efficiency.

To successfully accomplish the thesis purpose, the following specific objectives are identified:

- **The proposal of an energy performance assessment methodology** able to deal with data uncertainties evading non reliable evaluations. The methodology should contemplate multiple conditioning factors and be capable to create new scenarios based on historical data.

- **The proposal of a fast and reliable set point recommendation methodology** that take into account the operation limitations and the potential improvement capabilities. It should also consider operation trend classification, to minimize harmful actions to the machinery and achieve higher efficiencies.

- **The proposal of a load management methodology** that handles real-time load data to smooth and improve the energy efficiency, taking advantage of the individual cooling load consumptions.

- **The validation of the proposed framework** in the industrial refrigeration system defined as the case study of the present thesis.

In summary, the thesis pretends the proposal of an integral energy management framework focused on the highlighted aspects detailed above. The industrial refrigeration system employed for the validation is detailed in Annex I.

## 1.5 Description of chapters

A brief description of the subsequent chapters, in which this thesis is divided, is detailed below.

In Chapter **2. Data-driven energy management – state of the art**, a summary of the current literature regarding the energy management in industry is presented. The review is focused on the main topics presented in this thesis: the performance assessment, the set point recommendation and the load management. Each topic contains the ongoing research approaches with their drawbacks and limitations regarding generic energy systems and with further detail in the case study.

Chapter **3. Data-driven performance assessment** offers a detailed explanation of the benchmark creation methodology developed to obtain a reliable performance evaluation methodology taking into account the current state of the art shortcomings. Topics such as data-driven methods robustness, multivariable discretization or data proliferation are approached to attain the desired assessment. An experimental test, focused with the compressors efficiency, is also performed in order to demonstrate and validate the applicability of the proposed methodology.

The Chapter **4. Operation improvement: set point recommendation** explains the methodology adopted to suggest near-optimal set points to the system compressors. The chapter deals with the partial load problem, the set point stability constraints and the machinery switching issues to develop robust recommendations in industrial environments. The suggested methodology is also tested in the case study.

In Chapter **5. Load management**, the methodology to increment the system efficiency regarding the demand side management is presented. The chapter approach the non-intrusive load monitoring problem, also called load disaggregation, and performs a load balancing without conditioning the process schedules or the product quality. The load disaggregation is validated employing a simulated refrigeration system and tested under real conditions, while the load balancing is directly validated in the industrial case study system.

The Chapter **6. Conclusions and future work** contain the overview of the research contributions of this thesis and further promising paths to continue exploring in order to push forward the current dissemination.

In Chapter **7. Thesis results dissemination** lists the published manuscripts both at conferences and journals regarding this thesis results.

Finally, the **Annexes** illustrate and present an accurate detail of the real refrigeration system employed as case study and the mathematical simulation.

# 2.

## Data-driven energy management – State of the art

This chapter summarizes the current state of the art literature to tackle the energy management topic by means of data-driven methodologies. From the performance evaluation, passing by the operation improvement to the demand response management.

CONTENTS:

## 2 Data-driven energy management - State of the art

As has been aforesaid, data-driven energy management is a set of processes, based on data, that enable an industry or organization to implement actions in order to diminish the energy consumption and become more efficient. This novel data-driven paradigm is aligned with the framework of the Industry 4.0. Such framework exposes a set of technologies that allow the implementation of industrial data-driven schemas and exploit this information to provide process enhancements. A summary of such technologies and its integration in the process levels is depicted in **Fig 1.5.1**.

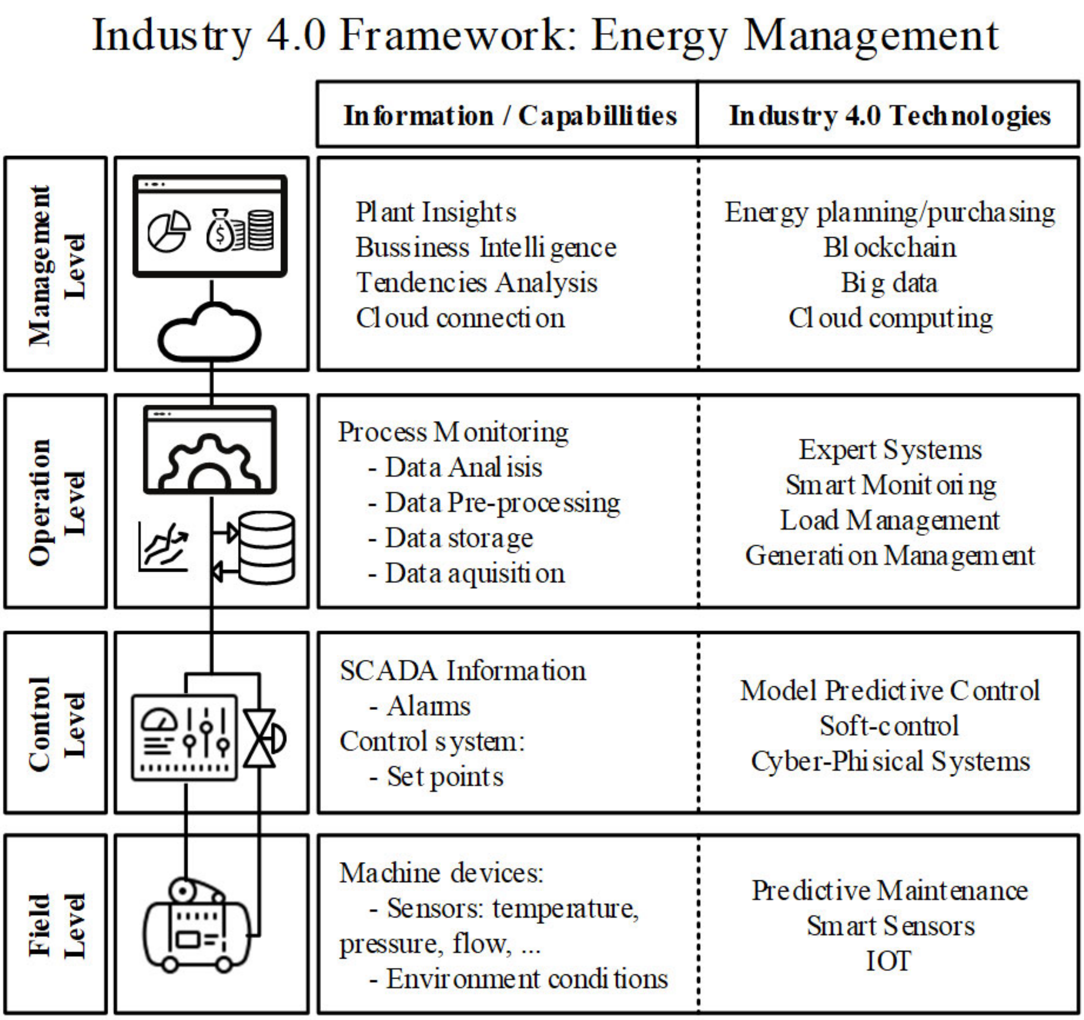


**Fig 1.5.1 - Energy efficiency within the Industry 4.0 Framework: Integration levels within the plant and its associated technologies.**

As one can see, the different technologies are related to the four different information levels that can be found in a factory. In this regard, the first level, the field level, corresponds to the technologies related with the standardization of the machines, processes information acquisition and the use of such data to perform on-site predictive maintenance actuations [34]. The most interesting technology of this level for the current thesis is the IoT, since it represents one of the key factors to allow industrial data-driven applications. IoT applied to process instrumentation, offers the opportunity to gather and store real-time data from any industrial process in a robust and standard way [35], [36], [37]. Therefore, the data acquired by IoT devices can be directly integrated in the energy management framework [38].

The control level in the Industry 4.0 focuses on how to use process data, control data and the information from the SCADAs to improve the classical control strategies. In this regard, the classical PID strategies have limitations in ruling the processes when the processes operate under uncertainties, in new conditions or under fast-changing conditions [39]. In such operations, the control strategies are improved by means of modelling the behaviour of the process with data-driven techniques and using such information to enhance the control. The most common method are the Cyber-physical systems, which use data from the process to develop a virtual twin of the process which is used to evaluate trends and tendencies improving with it the response of the control system [40].

The operation level is a key aspect of the Industry 4.0 for any energy management framework and it is the level where the approach of the current thesis is located. It deals about how to fuse process data from different sources to develop monitoring systems able to evaluate the current performance of the process under changing operation conditions [41], and how to use such information to develop expert systems that aid the workers to detect and correct any deviation from the optimal operation. In this regard, the aim of this thesis is to: (i) develop a methodology able to assess the current performance of the process, (ii) suggest the most suitable set points to increase the process efficiency, and (iii) manage the load to diminish the energy expenditure without affecting the product quality. These concepts will be explained in the following chapters of the thesis.

The management level in Industry 4.0 is focused on using process data to provide more reliable information to make business decisions for the company [42]. From this level, it should be remarked the efficiency of business intelligence [43] to improve the decision making and the energy purchasing strategies that use market tendencies to assess when to buy or sell energy for the company [44]. Since the focus of the thesis is how to develop energy management methodologies to improve the energy efficiency of the machines and processes within the industrial systems, this integration level is outside of the scope of the thesis.

Therefore, and as aforementioned, the focus of the thesis relies on developing various data-driven methodologies in this energy management framework for improving energy efficiency of an industrial refrigeration system. In order to tackle this topic from a literature point of view, three key aspects must be faced considering the necessities of an energy system, as shown in **Fig 1.5.2**.

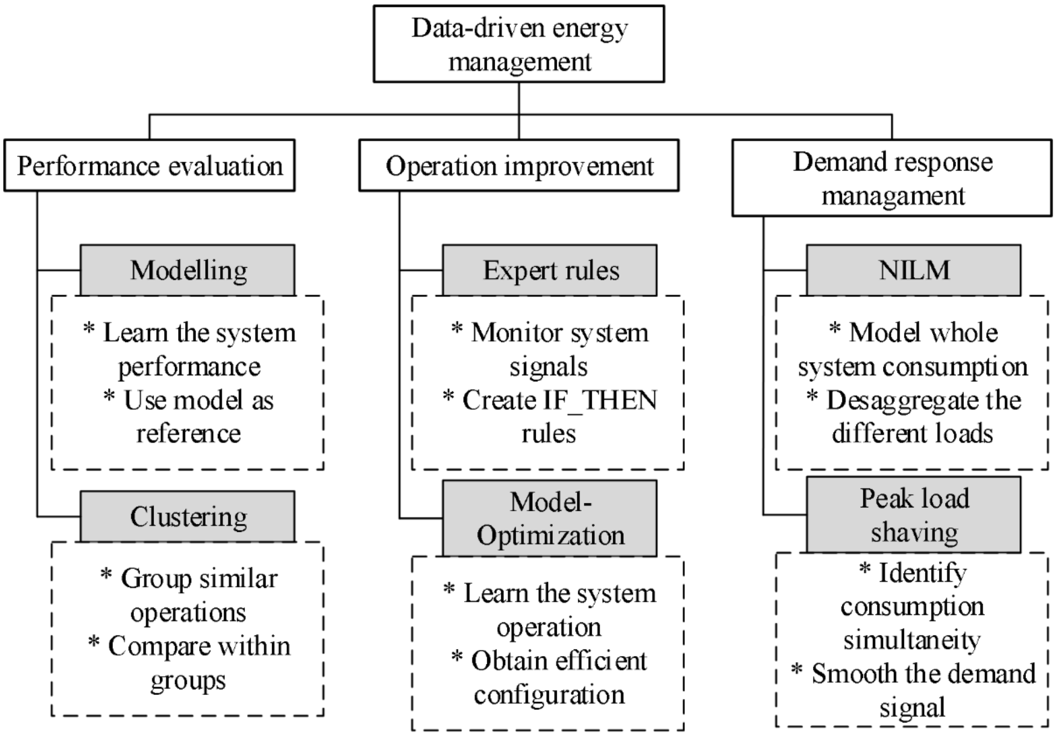


**Fig 1.5.2 – Data-driven energy management framework overview.**

Such aspects shown in the figure should be employed by any methodology for optimizing the energy efficiency. Further details and explanations of the aforementioned aspects as well as its current state of the art are presented below.

On the one hand, the efficiency evaluation and monitoring part is an extensive process composed, mainly, by two fields of study, the performance indicators and the benchmarking. The performance indicators, which can be considered the simplest method of benchmarking [45], are employed to specify a metric to measure the energy efficiency. These indicators can vary depending on the industrial system that is being monitored causing the creation of a multitude of different energy indicators [46]. The use of these indicators is highly related with the process being monitored and an adequate indicator for energy performance should be tailored to the explicit purpose [47]. The other field, the benchmarking, appears in literature regarding energy evaluation purposes [48]. The underlying idea in the benchmarking concept is to compare the evaluated process with a known process used as a reference. This reference can be an equal process of another company, the process itself compared with historical data or a similar process [46]. Both approaches aim to find a reliable consumption reference in order to evaluate the efficiency and both can be tackled employing modelling or clustering strategies which are further detailed below.

On the other hand, the operation improvement based on the monitored data is the future towards an efficient energy management system, focusing its efforts in the machinery set point adjustment [49]. The basic approaches are based to extract conclusions using the acquired data from the system but require expertise in the topic to formulate the improvement measures. While the advanced methods are based on the modelling of the system operation to subsequently find the best or a nearly optimal configuration from all feasible options [50]. The models of the data-driven strategies are based on the data acquired from the system which do not require expert knowledge to build mathematical or physical representations [51]. Whereas the optimization step, is commonly done with heuristics in order to search as fast as possible a suitable solution [52].

Finally, another way to improve the energy efficiency of a system is managing the demand response, technique that modifies the load consumption shape to enhance the performance. The basic step in this topic is to obtain a model of the connected loads, and it is still a challenging task to obtain due to the monitoring costs and the lack of datasets [53]. Although various NILM algorithms are proposed in literature to solve such problem, and these NILM techniques were first proposed nearly 30 years ago, several studies are still tackling this issue by means of this new data-driven and computational intelligence approaches [54]. Later, once the consumption of the loads is known, optimization algorithms are used to perform load shedding or shifting strategies in order to avoid peak consumptions [55].

Since each one of the energy management aspects presented in this thesis is a wide area of study, a more detailed summary of the current state of the art is presented below.

## 2.1 Energy performance evaluation

> *The main purpose of the energy performance evaluation is to identify the possible inefficiencies concerning the energy expenditure and to determine the potential energy savings taking for granted the supply necessities.*

In any kind of energy management strategy, it is indispensable to measure the current performance of the system. In this regard, the first step towards reducing energy consumption starts with the characterization of the system energy expenditure [56]. This energy characterization is the basis to develop further energy management methodologies and can be approached as a part of the process monitoring concept which includes the aim to avoid economic and energetic losses [57].

Taking advantage of the aforesaid energy monitoring concept, the amount of data collected in the industrial systems can be used to develop different data based methodologies to model and evaluate the energy performance. This energy performance analysis is an issue that affects a wide variety of research fields and can benefit several industries.

Typically, the energy performance in any equipment is determined by comparing the current consumption and the consumption obtained by a mathematical model in specific operation conditions [58]. As introduced in the chapter overview, the idea of comparing the performance with a reference model is known as benchmarking. Thus, in this new data-driven era, the benchmarking based with mathematical and physical models [59], [60], [61], [62] can be substituted by data-driven models or methodologies based on real operation conditions.

Various data-driven methodologies are proposed in literature to tackle such subject and are applied in a wide range of industrial systems and buildings using the advantages of the monitored data. These data-driven techniques, also called black box models, since they do not require any expertise on the system, can be divided in two generic groups for this specific performance evaluation purpose: the ANNs and the clustering analysis [63].

ANNs allow to model systems in which no rules that underlie them and that determine their behaviour are explicitly known, contributing to the resolution of scientific and industrial problems [64]. The ANNs can be used to model the performance of different industrial systems or buildings taking into account various external factors that affect the performance. These models created from data are used as benchmark to evaluate the performance of a system without the need of a physical model or simulation. However, in some studies, the data used to feed the ANN training is from numerical, simulated or even manufacturer data, with the drawbacks that this entails due to the impossibility to mimic real conditions [65], [66]. Otherwise, in situations where real data can be used to feed the model, it is required a vast amount of data, a proper network structure and a precise adjustment of its hyperparameters to guarantee an accurate output and avoid overfitting problems [67].

Other approaches such as [68],[69] discard ANNs due to its aforementioned overfitting problems and apply other non-parametric algorithms to model and cluster power curves. Clustering is in charge to divide data patterns into different subsets in such a way that similar patterns are grouped together [70]. Various authors use these clustering techniques to group similar energetic systems or buildings to be able to compare its performance among their closest neighbours within its cluster [71], [72]. These clustering approaches are also vulnerable to the hyperparameter selection and highly dependent on application characteristics and data [73].

E.H. Borgstein et al.[63], in their performance evaluation techniques review, summarize that data-driven algorithms are powerful when sufficient data is available and have great potential for improving the current evaluation performance strategies. Although, they remark that the lack of physical interpretation of the results may limit the effectiveness identifying energy performance improvements. Furthermore, other concern expressed by [74] is that the assessment of the model related uncertainty remain one of the strongest drawback in performance monitoring. Although multiple approaches based on data are being developed to evaluate the performance of energy systems, there is still way for improvement in order to develop a reliable methodology able to deal with the uncertainties and lack of robustness associated with these intelligent algorithms.

### 2.1.1 Case study: Performance evaluation in refrigeration systems

In vapour compression refrigeration systems, the most common measure used to evaluate energy performance analysis is the COP [75], shown in **Eq. 2.1.1.1.** This performance index, which measure the ratio among the useful cooling capacity ($Q$) versus the electrical input power ($W$), is the base of various performance studies such as [76], [77], [78], [79]. Apart from the peculiarity of this performance index, the data-driven techniques used to evaluate these systems are based on the same ANN and clustering approaches mentioned above, but adapted to the refrigeration systems.

$$COP = \frac{Q}{W} \qquad \textbf{Eq. 2.1.1.1}$$

Regarding to the ANNs group, some studies have developed models applied to this particular topic. Few of the authors tackle the problem comparing different refrigerant properties and performances, for this purpose, different modelling algorithms are used such as in [76]. In [76] authors compare two refrigerants using an ANFIS to model the performance of the proposed refrigerants employing the data from empirical tests in steady state. In this paper, the performance analysis core is based on different refrigerant properties and evaluated with the COP index.

In other studies, such as [80], various variables that affect the system are selected to model the consumption applying an ANN. Authors consider that the model can be used for determining the most energy efficient control algorithm. D.B. Jani et al. [81], also approach the modelling issue using an ANN applied to a solid desiccant cooling system at different operating conditions. Using the model, authors conclude that the solid desiccant based systems are energy saving and environment friendly. J.M. Belman-Flores et al. [82] evaluate the exergy assessment of a vapour compression system employing ANNs. Two networks are developed for each component of the system, one for the exergy destruction and another for the exergy efficiency and the data to train the networks is from an industrial refrigeration system. In all these aforementioned ANN approaches, which all rely on modelling the refrigeration system operation performance, common limitations appear concerning overfitting issues and the model reliability as it is not possible to know the performance under novel or not previous seen operation conditions.

With the clustering methods, other strategies have been developed to overcome the modelling limitations. F.W. Yu et al. [77], investigate the influence of components combination regarding the COP of a chiller system. The article is based on data acquired from a real chiller system with their respective water pumps and cooling towers. The authors identify the most important variables that affect the performance and cluster the system operation conditions. The study shows how linear models, network and survival analysis can assess the system COP both in steady and transition states. The paper is exhaustive regarding the variables used but it cannot evaluate the performance under not previously seen conditions.

Manfeng Li et al. [78] calculate the potential energy savings of a chiller system using the COP index and a clustering strategy. In this case, the data used is created with the simulation software Energyplus and grouped using a hierarchal clustering method. The methodologies based on simulations present drawbacks concerning the lack of adaptability to a real environment.

Yijun Wang et al. [79] base their methodology on the refrigeration system data but overcome the limitations of the data-driven methods creating a data proliferation Thus, authors create new operation conditions not previously seen on the historical dataset. The method does not require any modelling step and create different evaluation indexes to assess the actual operation. However, to create the artificially proliferated samples, some external factors that influence the performance are not contemplated.

Yijun Wang et al. in a following paper [83], tackle the limitations of their previous work creating a performance map of the chiller system under different operation conditions. Despite of the improvement of the methodology, still appear some concerns regarding the dependency of the modelling stage to create new data and the trade off in the range selection approach used to discretize the operation space, parameter which is directly related with the robustness of the performance assessment. As in the ANNs approach, the reliability of these techniques under novel operation conditions is one of the weakest points and in addition, the clustering method and parametrization selection affects the evaluation robustness.

### 2.1.2 Discussion and conclusions

In conclusion, despite this aforesaid performance analysis is the basis of any subsequent energy reduction method, various limitations appear in the literature in order to find a robust energy performance evaluation. An overview of the detected constraints found in the state of the art are listed below.

- The machinery manufacturers only provide operation model in nominal conditions and these are tested under a controlled environment which in most cases does not mimic the environment in industrial plants [84].
- Most of energy systems are composed of various machines from different manufacturers where each one provides the optimal operation specifications but it is not straightforward to quantify the performance of the whole system [85].
- It is necessary to take into account all the external factors that are related to the consumption to find out the possible energy savings that can be achieved [86].
- There are no practical recommendations selecting factors which influence the consumption and most of the techniques used as a benchmark to compare efficiency are simplified or do not contemplate the impact of these external operation conditions.
- Data-driven methodologies used to face this topic, present a lack of robustness when dealing with non-previously seen circumstances in the historical dataset [74],[76], [83], [80], [81], [82].
- The multivariable space discretization used by various authors [77], [78], [83] in order to be able to determine the performance under different operation conditions, can be enhanced as it is used as the basis for the performance assessment.
- Finally, the data-driven techniques which are populated with simulated data, lack of capability to resemble the real operation conditions and cannot be put directly into practice due to the differences among simulations and the real industry.

Concerning this energy analysis topic, it is appreciable that many efforts have been invested during recent years but still exist some drawbacks to be addressed in further studies. In this thesis, contributions to the performance evaluation in complex refrigeration systems under different operation conditions are proposed in order to mitigate the current state of the art constraints identified below. Such methodologies are addressed in Chapter 3 of this thesis.

## 2.2 Energy systems operation improvement strategies

> *The objective of the operation improvement strategies is to configure the machinery that produces the energy in such way that minimizes the resources expended to attain the desired demand.*

Energy efficiency is the basis in this smart industry paradigm in order to be competitive and sustainable. Several measures can be performed in order to achieve such goal as retrofitting or modifying the current systems employing time consuming and expensive variations [87],[88],[89],[90]. Other common approaches are based in fault detection [91], [92], [93], [94], which can be used to prevent costly incidents but do not improve the regular operation of a system.

In this smart factory environment, there is still few industries that explore the subtle but efficient measures that the data-driven algorithms and methodologies can provide to devise an optimal operation. The efficiency can be increased varying only some configurations of the already present industrial systems. This aforementioned data-driven based efficiency improvement techniques only uses plant data and operation constraints to suggest an ideal operation set points [95].

With this data, some studies have developed an easily interpretable IF-THEN rules to generate recommendations for control strategies [96]. Others, construct a model of the system response to subsequently perform the optimization of the controllable variables [97]. These strategies are applied in a vast variety of energy systems, a clear example of these easily interpretable rules is presented by Wen Tai et al. [98]. The authors implement an IF-THEN set of rules, created from the efficiency monitoring stage conclusions, and tested in a solar water heating system. Experimental results validate the effectiveness of the proposed method, nevertheless such validation present some shortcomings as it is only performed in a specific plant operation conditions and only grounded with the monitored data and the expert knowledge. In this IF-THEN rules scenario, all the proposed strategies to minimize the cost have to be tested in a real system in order to assert its functionality, with the problems that could induce to the industrial system if the strategy is erroneous. Furthermore, it is essential to be an expert of the monitored system to create the set of rules, fact which limits the applicability easiness.

On the other hand, the model-optimization approach to tackle such subject is more widely applied. Due to the vast amount of references related to this topic, some of the most common applications in literature are presented below to give an idea of the current strategies, applications and limitations in different energy systems. The modelling phase can be done using simulations, e.g. this this data-driven optimization methodology developed by [99] and applied to wind farms, employs a cooperative approach among all the wind turbines to increase its efficiency. The improvement is performed based in simulated operation data and employing an optimization algorithm.

Other ones use data to perform the model as in this analogous approach presented in [100], in this case the system to optimize is a combustion system of a coal-fired thermal plant and the model is performed with a data-driven modelling procedure. Alternatively, due to global optimum search problems and the time constraints, some authors such as Gong et al. [101] present advances to develop the optimization step. They firstly take into account different working conditions to improve the energy efficiency of an ethylene production process to model its behaviour. The method is based on the modelling and optimization approach but authors improve the performance using historical knowledge to achieve better results in the heuristic optimization and also to utilize less iterations to converge.

Although the current model-optimization methods present successful results, the nature of the optimization algorithms is slow due to its intrinsic iterations till the stop criteria or the convergence, causing an unfeasibility problem when it is applied to systems which require a faster response. Furthermore, the methods purely based on data-driven models present reliability problems as they do not contemplate non-previously seen abnormal or rare working conditions and its consequences  in optimization. Some authors [100], conclude that data-driven optimization strategies deserve more research efforts to be fully feasible in real industries.

### 2.2.1 Case study: Operation improvement in refrigeration systems

In regard to the studied systems, various data-driven operation improvement strategies have been developed in the current literature. As disclosed above, few authors take advantage of the monitored data to extract operation rules. These strategies are also applied in the specific studied case, to show an example, Alonso et al. [102], take advantage of the monitored operation data to create management rules based on their expert knowledge. The created decision rules decide which ones of the chillers of the facility need to be running in order to minimize the consumption.

Although the efficiency enhancements obtained, these type of methods cannot generate the rules automatically and the approach do not guarantee an optimal result as they do not use any kind of optimization algorithm. In addition, this methodology does not decide the partial load of each chiller, leading a huge room for improvement in regard to the efficiency improvement. These aforementioned PLR set point recommendations of each machine are difficult to tackle with the expert rules as the machines are constantly adapting its capacity to the demand necessities.

Otherwise, the vast majority of strategies to deal with this problem are based on the model-optimization concept. Various studies [103], [104], [105], [106] develop the model of the system using mathematical equations based on the acquired data from the process, to be able afterwards, to employ a heuristic algorithm to find the best available control parameters through various iterations.

Some drawbacks appear in these type of studies related to various factors such as their application in real-time systems, the computation time expenditure or the capability to take into account the physical constraints of the system. A few manuscripts are reviewed below to note such shortcomings presented in literature. For instance, in [103] authors do not provide further detail of how the methodology is implemented in real-time, the computation time or the physical constraints. In other study [104], the operation set points suggestion is performed with a far horizon such as one hour, making it unfeasible in real-time conditions due to the uncertainties associated with the cooling loads in a building or in an industry during that time. These long term set point proposals cannot maintain the desired comfort or temperature conditions of the refrigerated space and should require a more agile set point recommendation able to adapt the system operation to the current cooling load demand.

Other authors create methodologies to overcome the limitations of the pure data-driven models regarding their constraint of being unable to optimize the system in non-previously recorded operations. For example, in [105] the authors presents a methodology to enrich the data acquired in order to improve the modelling step. Despite the efforts applied to generate more samples, many shortcomings appear due to the enrichment strategy. To create these new samples in different conditions, authors changed the system set points randomly, technique that is non-viable in a real industrial system. Other papers such as Sohrabi et al. [106] apply these techniques in only a few steady state situations which cannot represent the entire set of possibilities that can occur in real operation conditions.

Despite the aforementioned methods to improve the energy efficiency and their shortcomings, other particularities that have to be taken into account appear regarding the refrigeration technology. Some system enhancement projects, also based in process modelling and a posterior optimization, try to improve the efficiency varying the system refrigerant temperatures and the mass flow rate in order to produce the same cooling load [103], [107], [108], [109]. These approaches can be only employed in certain type of refrigeration systems, commonly chillers where these variables are controllable. The case study of the overfeed system, despite being a refrigeration system too, cannot allow a mass flow variation in the evaporators due to the nature of the flooded technology used to ensure a great heat transfer.

Furthermore, in industrial systems where the most power consuming elements are the compressors, the discharge temperature is always as low as the system allows, in order to unload the compressors and reduce energy expenditure. And the suction pressure, which is the refrigerant temperature, is the one required by the industrial process load necessities. These aforesaid particularities make some of the current state of the art techniques unusable in the specific case study developed in this thesis.

Therefore, there is still way to go in order to obtain a data-driven methodology able to deal with such concerns. Industrial refrigeration systems, as the overfeed systems, do not hoard enough attention in the current literature and need a more detailed attention to improve its operation by means of data-driven strategies.

### 2.2.2 Discussion and conclusions

Current data-driven approaches to tackle industrial systems operation optimization still present some shortcomings in order to be fully applicable in real conditions as stated above in the literature review. The set point improvement proposals presented in the state of the art are composed of two main stages which are highly interrelated to obtain a reliable solution: the modelling and the optimization.

- The modelling step is the basis of the optimization process as reproduces the system operation response when different configurations strategies are tested. Such models can be developed with mathematical equations or simulation software with the drawbacks that this entails due to the differences of the ideal system in regard to the real system [110].
- Physical modelling is non-viable in complex industrial systems which are composed of different machinery, several conditioning parameters and dynamics difficult to resemble [111].
- The other manner is the data-driven algorithms which model the system behaviour from the data acquired. These algorithms can identify the underlying system behaviour without the need of expert knowledge of the process.
- The main deficiency presented by these techniques is the lack of generalization capabilities as the model commonly overfit the system behaviour to the data used to train.
- This overfitting feature limits the improvement potential as the search space of the optimization algorithm is restricted to the historical operation data in order to be trustworthy.
- Regarding the optimization using the expert IF-THEN rules, the suggested optimization measures extracted via the data analysis are always constrained to the expert who designs them and their knowledge [112]. Even though the expert master the subject, it is difficult to get a near optimal operation configuration with some rules of thumb due to the vast quantity of signals and conditions involved in an industrial system.

- The optimization based on algorithms can achieve a major improvement at the expense of computing time. In some studies, these techniques are only applied in a specific test conditions or assuming steady operation during large amount of time in order to validate its efficiency, being totally impossible to extrapolate to the vast operation conditions and demand of a real industrial systems.

- Other approaches are based in heuristic algorithms which are continually searching the optimal configuration parameters. Although some heuristics present great results optimizing parameters, the time needed to calculate the result over various iterations remain a problem in dynamic processes where the controlled magnitude deviation is very critical [113].

Regarding the exposed literature issues, the proposed thesis presents a robust data-driven methodology recommending near-optimal set points for the compressors involved in the system. Such recommendation considers new near-optimal scenarios never seen in the historical database obtaining the benefits of the data based techniques and overcoming the historical operation overfitting limitations. Furthermore, the methodology estimates the supply requirements trend to add robustness to the recommended set points and avoid time consuming calculations which makes it feasible to apply in a real-time scenario. Further information of this subject is given in Chapter 4.

## 2.3 Demand response management

> *The demand response management makes reference to the modifications made in the power consumption pattern of a customer to improve the efficiency of the whole energy system, composed by the demand and the supply sides.*

Two main approaches are presented in literature regarding to this topic, the ones that the customer operation is modified via price based programs and the others that are based in incentives [114]. The price based approaches are out of the scope of the thesis due to its impossibility of application in the analysed case study. Concerning to the incentive based, the essential step starts with the identification of the power consumed by each load connected to the system in order to apply the subsequent management strategies. Such task of load monitoring is, in most industries, totally unaffordable due to the investment cost for metering the aforementioned loads making the demand management non-viable [115]. To tackle such problem, NILM techniques, also called energy disaggregation, are being researched taking advantage of the advances in computational intelligence and IoT [116].

In regard to the NILM topic, several approaches are presented in literature depending on the load type: ON/OFF, finite states or continuously variable [117]. Whereas ON/OFF and finite state loads modify its consumption signal in a clear step, the continuously varying loads show a smooth pattern. These continuously variable loads are the most common in industrial and commercial applications [117] and also, the most challenging ones for the disaggregation task [118]. Although the NILM approaches pretend to use only the aggregated consumption data from the system or the household, in practice, most of the state of the art proposed solutions are supervised, which means that they require data from the specific loads in order to train the method [119].

On the other hand, unsupervised techniques can be grouped into three subgroups according to the data utilization. The first one uses unlabelled training data to build the models, the second one uses labelled data from a known system to create the models and then these models are tested in unknown systems and finally, the third one are the techniques that do not require any kind of training [120]. The ones that use unlabelled data are more suitable in industries where different processes signals are available in their SCADA and databases whereas the ones that use labelled data from a specific system to extrapolate the results in similar situations are more expensive and also more overfitted to the data [120]. Regarding the totally unsupervised approaches, some studies reflect that perform poorly with the non-principal loads [120] and also perform worse than the other unsupervised groups [121].

Concerning the load management, different peak load shaving strategies are reviewed to attain an efficient energy utilization [122]. All these approaches to minimize the peak consumption can be grouped into three main categories: the load shedding technique which consists in turning off some loads, the load shifting which distributes the loads among time to reduce the peaks and finally, hybrid techniques which combine both concepts [123].

Data-driven techniques are also being applied in this topic due to its capability to model complex systems and provide optimal shedding and shifting strategies, however the lack of generalization and its low response limit their usage in real implementations [124]. Furthermore, most of these demand response optimisation studies have been done for residential consumers while more research effort is needed in industrial environments [125]. In industry, concerns such as the interdependencies among machines or the wide variety of processes, make totally impossible to design a universal demand response program [126].

### 2.3.1 Case study: Demand response management in refrigeration systems

In refrigeration systems, the thermal inertia is used to apply different demand response approaches such as load shifting and shedding in order to balance the power consumption [127]. To be able to manage the loads in real-time of a refrigeration system, and be able to operate the whole system in optimal performance, which means higher COP, thermal loads of each refrigerated space should be identified. Therefore, the NILM topic applied in different electric appliances can be extrapolated to this refrigeration terrain.

Regarding to the aforementioned energy disaggregation in refrigeration, few studies are found in literature and additionally, most of the current manuscripts put its efforts to disaggregate the electrical consumption of the refrigeration machinery [128], [129] and not to the thermal load, also called cooling load in refrigeration. Other articles divide the whole cooling load of a system into various estimated sub-items such as the conduction, solar, air or internal loads of a whole building [130], [131] but omit the discrete consumption of each refrigerated space or even each cooling machine.

On the other hand, regarding the demand management, the spaces to refrigerate should maintain a certain temperature, and are typically controlled by a deadband, which means that the evaporators turn on when the temperature reaches the upper limit and turn off when they reach the lower limit. Hence, the cooling capacity is used randomly as well as the energy consumption in order to supply the demand necessities [132]. To improve such operation, and avoid non-desired consumption peaks, several studies are presented; from TESs such as PCMs to accumulate the energy [133], to MPC strategies, which use forecasting information to anticipate the demand behaviour. In these approaches, most of the cooling loads are mathematically described by the ETP models [134], using software such as TRNSYS and EnergyPlus or using data-driven techniques to model the load behaviour or even to identify the ETP equations parameters [135].

In this regard, data-driven load management relies on the operation control of the machinery or changing the set point of the temperature [136]. Contrarily to the thermal comfort in buildings, which is the main concern in the applications of refrigeration in the state of the art, in industrial processes the principal target is the final product quality, which is stricter with the temperature constraints. Hence, in industrial environments, the set point within its deadband cannot be changed and also should be assured in order to avoid possible final product quality issues.

Moreover, most of the state of the art load management techniques that are applied in buildings are based on the usage of the aforementioned forecasting models[137],[138],[139]. Such applications take advantage of the periodicity in the load to model the behaviour and manage the loads in consequence. However, other characteristics that affect industrial refrigeration systems, such as various spaces to refrigerate in parallel or huge cooling loads that appear randomly due its nature, can hinder the forecasting reliability and the subsequent demand management. These particularities, difficult the application of methodologies that incorporate forecasting in delicate refrigeration processes, since the errors associated with the forecasted signals can affect negatively the management and compromise the product quality.

Finally, another relevant issue that appears in literature related with the uncertainties associated with the methodologies that incorporate a forecasting step is the cold load pickup problem, which is the peak load that appear when all the previously stopped machinery is restored to operation [140]. Such problem is not avoidable in situations where the cooling load appears randomly but can be reduced if the management strategy does not include errors induced by the forecasting that suggest a pickup in a non-necessary situation.

Therefore, the methodology should avoid such forecasting approaches and apply an adaptive solution able to adjust the management in every instant according to the variable load necessities of an industrial refrigeration system.

### 2.3.2 Discussion and conclusions

As a conclusion of the state of the art, there is evidence that there is a huge difference in the NILM research efforts applied in electrical loads compared with cooling loads. Moreover, regarding the load management techniques, most studies are focused in thermal comfort instead of industrial applications, where the goal is to guarantee the product quality and the constraints are stricter. The main identified drawbacks of the current state of the art are listed below:

- NILM techniques in the state of the art only focus its efforts to disaggregate electrical loads not taking into account the cooling ones.
- Cooling loads are basically modelled using physical equations or simulation software. More research is needed to perform data-driven modelling using real-time data [141] or to disaggregate cooling loads.
- The use of storage technologies in order to save energy in low demand periods can be detrimental regarding the increase of cooling losses.
- Moreover, predictive techniques, used to apply load management strategies such as shedding/shifting algorithms, are highly dependent on the goodness of the forecast [33].
- Without robust load information of the temperatures and loads behaviour, all the proposed predictive management methods, either storaging the energy or controlling the appliances, are constrained to the modelling errors.
- These errors could provoke non-desired load pickups or extra energy costs, and in most scenarios, deviations from set points which can lead to a product quality issue.
- Data-driven load management is a challenging topic which require a deeper focus in real-time methodologies in order to avoid the forecasting error constraints, deal with the uncertainties of the system, and its computational complexity [142].

Although many achievements have been made during recent years in demand response management of electrical loads, there is still a gap in order to apply most of the state of the art techniques to refrigeration systems in an efficient way, which is in the scope of the proposed thesis. The proposed methodology employs the available variables of a refrigeration system to estimate the consumption of each individual cooling load. Moreover, the management of such loads is proposed without the usage of forecasting assumptions which lead to a more robust management. All these approaches are addressed in Chapter 5 of this document.

# 3.

## Data-driven performance assessment

This chapter presents the proposed methodology to evaluate the compressor performance employing historical operation data. Paying special attention to the assessment robustness and reliability, as well as the capability to artificially create a broader casuistry of performance samples taking into account the system conditions.

CONTENTS:

# 3 Data-driven performance assessment

This chapter deals with the development of a data-driven performance assessment methodology regarding the aforementioned case study of the industrial refrigeration system. The outlined limitations reviewed in the state of the art chapter are basis for the proposed methodology described in this section of the thesis. The presented solution aims to assess the system performance in a robust and reliable manner overcoming the typical data-driven strategies drawbacks of the literature.

## 3.1 Introduction

This section summarizes the background and motivation for this particular research topic as well as the explanation of the innovative contributions of the proposed methodology.

### 3.1.1 Background and motivation

The performance assessment is a critical aspect in any energy system as discussed above in the state of the art chapter. This critical importance lies in the fact that this topic is considered the foundation of the subsequent improvement methodologies. The performance evaluation conforms the basis of the potential improvement capabilities of the system and quantify the current operation losses. In this smart industry era, the capability to take advantage of the monitored data in industrial processes makes feasible the development of new solutions to tackle such problem using data-driven methodologies. This fact opens a new field of opportunities which need further research, in order to be fully applicable in real conditions, and still present room for improvement.

In refrigeration systems, and more particularly in the overfeed vapour compression systems, the application of this aforementioned topic suppose a challenging task due to the multiple machines that are involved in the refrigeration process and the various features that affect its operation. Typically, machines manufacturers provide information about the performance of each device in optimal operation conditions, which, in most cases, do not represent the real working conditions in industry.

Ideally, these refrigeration systems should be designed to operate in full load conditions, the settings for which the manufacturer designs the machines, but in the end almost never operate in this way due to the demand variability. In such scenario, the manufacturer does not provide any performance information as it would require further extensive tests under different installation conditions. In addition, even though the manufacturer could supply a full map of operation performance it would not be useful in such installations as the dependence among the different machines that compose the whole refrigeration system mask the optimum performance achievable.

Regarding these machines performance, in refrigeration systems, the device that consumes the vast majority of electrical power is the compressor. In a common industrial facility various compressors are allocated in parallel to be able to supply a huge amount of cooling capacity. Therefore, the performance of the whole system is highly dependent on the compressors configuration. Furthermore, the aforesaid compressors can view its consumption greatly affected due external factors such the suction and discharge pressures. Hence, the task of evaluating the system performance without taking into account all the operation conditions would lead to an unreliable assessment.

Aside from the multiple intrinsic aspects that affect the performance of refrigeration systems stated above, the fact to face such topic using data-driven techniques add some inherent shortcomings associated with this techniques nature. The data-driven strategies are constrained to the data which are developed for. This means that the performance evaluation implemented using these techniques cannot be reliable in non-previously seen scenarios, obtaining thus a misleading assessment. Moreover, it is not possible to quantify the real potential improvement capabilities if the system has never operated with the best configuration and the suggestions are limited by the historical experiences, which can provide a valuable improvement potential but still have room for enhancement. Hence, it is easy to underestimate the potential improvement using such approaches.

In conclusion, the performance assessment taking into account the operation variability of the refrigeration systems regarding the different machines configurations and the continuously fluctuating load, along with the numerous operation factors that affect its performance, compose a challenging task. Additionally, data-driven methodologies still present some limitations such as the bias induced by the historical data and the inability to deal with new behaviours, that need to be further studied in order to provide a reliable performance assessment.

### 3.1.2 Innovative contribution

The proposed methodology to tackle the performance evaluation topic push forward the current studies in this field, overcoming some of the limitations stated above such as the evaluations without taking into account all the affecting variables or the intrinsic data-driven approaches problems which reduce the robustness of the assessment. The suggested solution evaluates the compressors performance employing only the historical operation data and avoiding manufacturer information or mathematical simulations. Thus, ideal system models or manufacturer information that do not mimic the real operation are dodged and the methodology is capable to fundament its assessment based on the real system information.

The presented procedure pretends to evaluate the performance taking into account all the external variables that affect its operation giving special attention to the reliability of the assessment. Therefore, the operation space is segmented according to its conditions.

*The **benchmark** should be able to **assess the performance** of an industrial refrigeration system composed of **various machines,** and capable to identify and take into account **different operation conditions**.*

In this aspect, an outlier detection algorithm combined with the aforementioned operation segmentation technique, ensure the reliability of the evaluation decision and avoid uncertainties. Thus, the system is always evaluated against samples within the same operation conditions and the non-trustworthy evaluations are identified avoiding misconceptions about the system performance or improvement capabilities.

*The methodology should **grant a robust evaluation,** managing non-previously seen or poorly represented operation conditions to **avoid uncertain** results, which are not admissible in industrial refrigeration systems.*

Furthermore, to reduce the constrains of the data-driven techniques, which are commonly limited to the already seen situations, a proliferation strategy is performed under each space segmentation. As the compressors configuration is linearly independent under the same operation conditions, several combinations are employed to increase the historical dataset scenarios. Thus, new artificially generated samples are created based on the real historical operation obtained from the database. In this manner, a broader benchmark is achieved being able to obtain, in some scenarios, even better performances under each operation conditions than the ones presented in the historical dataset.

*The assessment **benchmark** must overcome data-driven historical constraints determining **new** attainable **performance** scenarios **within each operation condition**.*

In conclusion, the proposed methodology elaborates a performance evaluation model that takes into account all the factors that affect the performance, the uncertainties associated with the data-driven techniques and is capable to boost the historical scenarios in each situation via the proliferation. Once the performance evaluation model is created, it can be used with new data as a benchmark to assess the system efficiency or even to evaluate further management strategies.

## 3.2 Performance assessment methodology

To create the performance assessment procedure, which is used as the basis for the subsequent evaluations, the methodology depicted in **Fig 3.2.1** is proposed. The method is basically divided in three main blocks: the first which deals with the operation discretization robustness, the second which is in charge to find the best performance under each discretized conditions and the third which uses the benchmark to assess new samples.

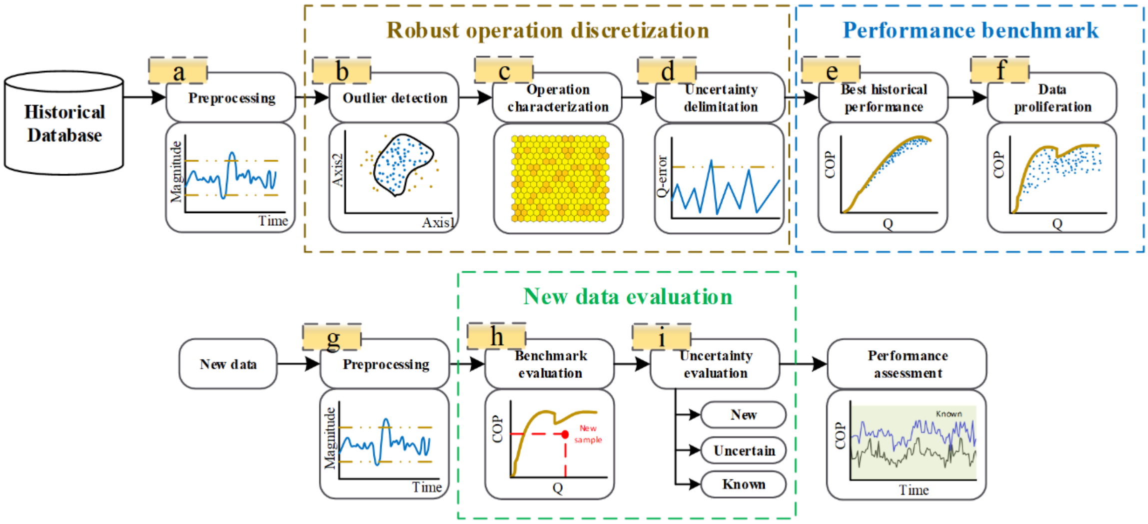


**Fig 3.2.1 - Performance assessmentn methodology overview.**

Initially, since the proposal is totally grounded on data, all the system related data is extracted from the database and afterwards preprocessed in (a) to delete non-possible samples according to sensor ranges and system experts' knowledge.

To begin with the first block, and employing the remaining data from the previous step, an outlier detection algorithm (b) is applied to separate the non-common operation conditions from the regular ones, which can lead to an erroneous assessment due to the lack of information. Furthermore, the presence of outliers can deteriorate the subsequent modelling. This outlier step is a tool in charge to attain the desired robustness of the methodology, however, in order to assess the system operation performance, it is necessary to model its operation conditions that affect its efficiency.

The aforesaid modelling (c), has the purpose of characterizing the system operation and is performed by means of a segmentation technique. This technique, which discretize the operation space, is in charge to perform a discrete and finite modelling of the process operation. Due to the complexity of the system, it is more efficient and provide more reliable results the discretization approach rather than a continuous model. The usage of an infinite set of continuous states can lead to modelling errors and uncertainties which do not reflect the best benchmark system performance achievable. Furthermore, employing this approach, it is possible to select the best performance and employ the proliferation step described below within each discrete process operation conditions, which is not possible in an infinite set of continuous states scenario.

To develop the aforementioned discretization, the common conditions data from the outlier detection step is used. A SOM is applied to discretize the system operation space, thus in each neuron of the discretized grid a reliable comparison among samples can be made. At this step, due to the capacity of the SOM to adapt the position of its neurons to the high density areas, and the previously performed outlier removal procedure, a robust discretized grid is obtained.

However, to ensure the reliability of the assessment when the method is applied with new samples, two uncertainty delimitation thresholds (d) are developed taking advantage of the previous outlier detection. Such thresholds are developed to provide information of how similar is the evaluated sample in regard its representative neuron and to avoid the outlier detection step in the new data evaluation part. In this manner, each new assessment provided by the methodology can be labelled with an uncertainty tag, avoiding unrealistic or non-reliable evaluations where the conditions are not comparable.

With the robust space discretization elaborated, the next step which is the second main block of the methodology, consists in determining the benchmark performance on each discretized area. Either one of these areas contain several samples that are similar among them according to its operation characteristics but different respecting their performance. Thereby, the best COP curve from the dataset in each discretized area is obtained (e), which reflects the best historical compressors configuration under that conditions. The illustration **Fig 3.2.2** depicts the aforementioned discretization with its benchmark performance line for each discretized area (DA) where the operation conditions are similar.

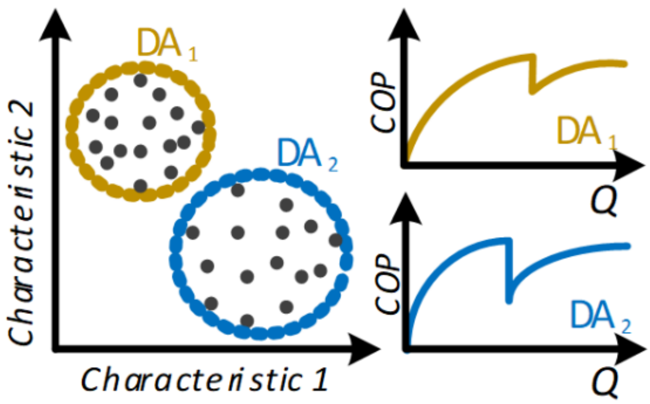


**Fig 3.2.2 - Exemplification of a COP lines of two discretized areas of operation.**

Till this step, the method is able to obtain, in a robust way, the best historical compressors configuration taking into account all the relevant factors that affect its performance, but is limited, as most of the data-driven techniques, to the past experiences. The last step consists in proliferate the samples under the same discretized area (f), that means to create multiple combinations of machine configurations seen in the historical dataset in order to obtain more efficient performance curves. These performances have not ever happened in the real system but they can be assumed as possible as the compressors are linearly independent among them within the same operation circumstances. Thus, an even better benchmark than the one obtained from the historical dataset can be achieved and it is possible to avoid the bias induced by the operating strategy of the compressors.

Finally, when the benchmark is already created, the method is used with new data, which is the aforementioned third block of the methodology. In this block, the new data, that can be obtained in real-time from the refrigeration system or from past operation periods, is evaluated to assess the system performance. First of all, in (g), the new samples are preprocessed with the same strategies as in (a) to dismiss measurement errors. Subsequently, in (h), the new sample is mapped to the discretized grid in order to find the best performance curve regarding its operation conditions. With this assignment, the new sample can be compared with the benchmark taking into account the variables that affect its operation. Ultimately, before assess the system, the sample is labelled according the uncertainty thresholds delimited previously. With this action, the final assessment provides information about the reliability of the comparison.

This new data block allows to evaluate the refrigeration system performance in real time or perform a forensic analysis, assuring its reliability with the uncertainty delimitation. Further details of each block are described below, as well as the experimental results in the real refrigeration system.

### 3.2.1 Dealing with robustness in performance assessment

In most data-driven techniques, the robustness term is referred to the effectiveness of an algorithm or methodology against new data or slightly variations regarding the data for which was trained. Hence, the capability to detect outliers, samples which are significantly different than other observations from the dataset, is a fundamental feature to take into account regarding the robustness aspect. Data samples which are not enough represented in a dataset are difficult to model due to the lack of information about them. Hence, the robustness of any data-driven strategy in these non-well characterized areas of the dataset space can compromise the methodology outcome.

Specifically, in performance evaluation methodologies, it is imperative to detect such abnormal or non-common samples in order to provide a trustworthy performance measurement. In the proposed methodology, various strategies are used to deal with this concerning aspect. From an outlier detection algorithm at the beginning of the methodology, to various uncertainty thresholds to ensure the quality of the assessment, passing by a self-adaptive space segmentation to contribute with more resolution and granularity in the denser information areas. A more detailed explanation of the steps regarding the robust operation discretization block is presented in the subsequent sections.

### *3.2.1.1 Outliers detection*

With the preprocessing step already performed, which is implemented to remove the already known erroneous samples, the next part consists in identifying the outliers. This outlier recognition divides the dataset in two subsets: the common or “normal” set and the abnormal or “novel” set. The normal set represents the common operation of the analysed system and is used in the next steps to develop the characterization of the system operation. Otherwise, the novel set defines the operation that rarely occurs in the system and is utilized to define the novelty threshold, which is used in the next steps to label the level of uncertainty. The uses of both sets are accurately explained in next sections.

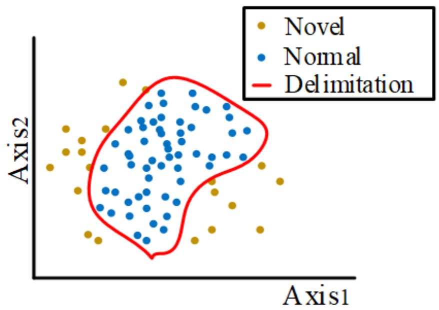


**Fig 3.2.3 – Illustration of a typical outlier detection delimitation.**

Regarding the distribution of the number of samples between both sets, does not exist a rigorous recommendation in literature. This parameter is defined by the probability density function and the outlier threshold proposed, which in standard situations lead to around 90% of the data to the normal set and 10% to the novelty set. Nevertheless, these proportions are limited to many circumstances, included the integrity of the database, length of the analysed period, distribution of the data, etc.

To implement this outlier detection step, the statistical non-parametric anomaly detection MVKDE algorithm is used. The MVKDE also known as Parzen windows or Parzen-Rosenblatt windows, is a flexible approach to estimate the densities of a given multi-dimensional data distribution [143]. Given a $d$-dimensional vector $\mathbf{X} = (X_1, \dots, X_d)^T$ where $X_1, \dots, X_d$ are one-dimensional variables, the vector $\mathbf{X}_i$ represents the $i$-th observation of the $d$ variables:

$\mathbf{X}_i = (X_{i1}, \dots, X_{id})$, where $i = 1, \dots, n$, and $n$ correspond to the total number of observations. The variable $X_{ij}$ is the $i$-th observation of the variable $X_j$, where $j = 1, \dots, d$. The PDF of $\mathbf{X}$ is, then, given by the joint PDF of the random variables $(X_1, \dots, X_d)^T$:

$$P(\mathbf{X}) = P(X_1, \dots, X_d) \qquad \textbf{Eq. 3.2.1.1}$$

Kernel functions are applied to scale distances. For example, in a one-dimentional case where $u = (x - X_i)/h$, the $h$ is the smoothing parameter called bandwidth, and $x$ is the currently analized observation. In the multivariate version, the bandwidth can be set individually for each distance $(x - X_i)$, obtaining a $d$-dimensional bandwidth $\mathbf{h} = (h_1, \dots, h_d)$. There are different approaches to form a multi-dimensional kernel, $K(\mathbf{u}) = K(u_1, \dots, u_d)$, is an example of a multiplicative kernel, $K(\mathbf{u}) = K(u_1) \cdot \dots \cdot K(u_d)$. Using this approach, the density estimator can be given as in **Eq. 3.2.1.2**.

$$P_{\mathbf{h}}(\mathbf{x}) = \frac{1}{n} \sum_{i=1}^{n} \left\{ \prod_{j=1}^{d} h_j^{-1} K\left( \frac{x_j - X_{ij}}{h_j} \right) \right\} \qquad \textbf{Eq. 3.2.1.2}$$

The PDF highly depends on the selection of the bandwidth parameter vector [143]. A performing approach is to set the bandwidths through the least squares cross-validation. By this approach, each bandwidth $h_j$ is selected so to minimize the integrated mean square error between the estimated and actual distributions as in **Eq. 3.2.1.3**.

$$IMSE(h_j) = \int \left\{ P_{h_j}(x_j) - P(x_j) \right\} dx \qquad \textbf{Eq. 3.2.1.3}$$

In this particular problem, this multivariate hyperparameter tuning is beneficial for the proper selection of the anomaly boundary. Therefore, the chosen algorithm is selected as it can be optimized for each variable of the space in comparison with other classical techniques such as OCSVM [144], which hyperparameters are unique regarding the number of the variables analysed. Furthermore, as it can be seen in the exhaustive study made by Domingues et al. [145], the selected algorithm presents a high robustness against noise, high dimensionality and stability. As a drawback, must be said that this technique is computationally expensive but in the proposed methodology is not a problem as it is only used during the creation of the performance assessment benchmark, not in the new data assessment.

### *3.2.1.2 Discretizing the operation space*

Taking advantage of the “normal” dataset extracted from the previous step explained above, the discretization of the operation space is developed. This discretization consists in a clustering algorithm capable to separate the system operation conditions among various groups. This clustering is the basis of a reliable and robust benchmark, hereby, the outlier detection step is performed before this discretization as the non-representative data can affect the clustering performance negatively. In addition, the difference among the samples within the same cluster can also influence adversely the reliability of the assessment, providing performance comparisons with non-enough similar samples. To approach such issue, the SOM algorithm is employed due to its ability to tackle the aforementioned concerns.

SOM neural networks, also known as Kohonen maps were first proposed by T.Kohonen [146], in 1990, and were initially used to build a topology preserving mapping. The grid of this kind of neural network tries to conserve and allocate its neurons position preserving the topological properties of the input space. The output space, also called mapped space, latent space or grid, is a parameter to be determined. The most common output grid dimensionality is composed of two or three dimensions, which are enough and suitable for most of the applications [147].

The SOM grid is formed by various neurons also called MU. Every MU has its own D-dimensional weight vector $w_{v\text{-}j}$, where the *v-th* represent the data and *j-th* the neuron. This weight vector is the neuron coordinates in the input space. The assignation of each data point $x_{v\text{-}i}$ to one of the grid neurons is the mapping action, the selected neuron is the one whose weight vector is closest to the data point, called the BMU. In the output space, the position vector $y_{v\text{-}i}$ is given by the weight vector of the selected BMU. The error function ($E_{SOM}$) used is shown in **Eq. 3.2.1.4**. This error function comes from the basis that an initial topology of the SOM network should be defined, usually as a rectangular or hexagonal grid. Then, the training algorithm tries to minimize the changes of the initial network while adjust the position of the MU’s to the input data space.

$$E_{SOM} = \sum_{j} \sum_{i \in s_{y-i}} \left(w_{v-j} - y_{v-i}\right)^2 \qquad \textbf{Eq. 3.2.1.4}$$

Where $s_{y\text{-}i}$ is the set of data points which have neuron $i$ as closest neuron. This error metric represents the average squared distance from the data point to its representative neuron. The objective of this technique is to minimize this error function in order to distribute the neuron grid over the input space preserving the topological properties of the original distributed grid. This minimization is performed updating the weight vectors $w_{v\text{-}j}$ of the neurons and it can be implemented using the classical gradient descend approach:

$$w_{v-j}^{(t+1)} = w_{v-j}^{(t)} - \alpha^{(t)} \left(\nabla E_{SOM}^{(t)}\right)_{v-j} \qquad \textbf{Eq. 3.2.1.5}$$

The learning rate is not useful in such algorithm as it does not depend on the output space and does not take into consideration the neighbour neurons. Hereby, the learning rate is substituted with the neighbourhood function $Nhf_{wn}$ which depends on the mapped space:

$$Nhf_{wn}^{(t)} = \begin{cases} \alpha^{(t)} & if\ i \in N_{wn}^{(t)} \\ 0 & if\ i \notin N_{wn}^{(t)} \end{cases} \qquad \textbf{Eq. 3.2.1.6}$$

Where only the nearest neurons with a certain range of the BMU in the output space are considered, $N_{wn}^{(t)}$. In this way, while executing the training phase the *α(t)* decrease monotonically and the neighbourhood among the neurons in the input and output spaces is preserved.

It should be noticed that the error metric presented in **Eq. 3.2.1.7** is used for the internal adjustment of the grid, but it is not representative if the SOM map is well adjusted to the input data. In this regard, the algorithm training performance is evaluated using the average quantization error (*Qerror*) (4). This metric evaluates the average distance between each input data vector with the selected BMU, where *N* is the number of sample vectors in the input data $x_i$ .

$$Q_{error} = \frac{1}{N}\sum_{i=1}^{N} \|x_i - BMU_i\| \qquad \textbf{Eq. 3.2.1.8}$$

Thanks to this SOM algorithm, the system operation is characterized with a 2D grid of neurons. Each neuron adapts its position to the feature space preserving as much as possible the original topology with its variance, information and distribution. Thus, each neuron, also called MU, describe a specific operation area of the system. Hence, the MUs are used in the proposed methodology to describe a specific operation conditions of the system and provide the capacity to develop a reliable benchmark taking into account all the variables from the input space that affect the operation performance.

As a clustering technique and although it is demonstrated that do not exist an algorithm capable to perform uniformly good under all datasets, applications and circumstances [70], this NN is selected due to its ability to represent with more resolution the densest areas, its topological preserving properties which provide semblance among nearest MUs and its dimensionality reduction capabilities [148]. In addition, the aforementioned *Qerror* measure gives the possibility to identify the degree of similarity between the evaluated samples and its BMU, property that the following section takes advantage in order to give robustness to the methodology.

#### *3.2.1.3 Uncertainty delimitation*

It is important to notice that the system operation clustering performed in the previous step, since is based with empirical data, cannot contemplate all the possible scenarios that could occur in future conditions. Therefore, to provide awareness of the performance assessment reliability, a module of uncertainty detection is included in the proposed methodology. This uncertainty delimitation is performed to detect deviations or new operation conditions of the system not reflected in the "normal" dataset for which the discretization was made. This measure, provides robustness to the assessment method and awareness of the system deviations.

For this uncertainty measure, the SOM *Qerror* is used to label new scenarios according to their value, a high *Qerror* would imply that the analysed measurement corresponds to new conditions not previously considered in the training set, and a low *Qerror* would imply that the data correspond to the known operation conditions. For this reason, to easily interpret and label the uncertainty of evaluated measurements, two thresholds are defined according to the *Qerror* to obtain three labels: known, uncertain and new.

The first threshold, $Th_1$, is obtained by analysing the *Qerrors* obtained on the normal set. This threshold represents the first boundary that separates data considered known and data considered uncertain, therefore the known concept is limited to data used in what its considered normal.

$$Th_1 = \max\big(Qerror(Normal\ Set)\big) \qquad \textbf{Eq. 3.2.1.9}$$

For the second threshold, $Th_2$, the "novel" set extracted from the outlier detection step is evaluated by the trained SOM with the "normal" set, therefore higher *Qerrors* are obtained which reflect values corresponding to data that have already been considered an outlier or new. Consequently, this threshold **Eq. 3.2.1.10**, where $\sigma$ represents the standard deviation, with a higher value than $Th_1$, explains the limit between uncertain and new. Therefore, data between $Th_1$ and $Th_2$ is considered uncertain and data with higher *Qerror* than $Th_2$ is considered new. For this second threshold, the standard deviation measure is used since it is commonly used to detect deviations in datasets [149].

$$Th_2 = 3\sigma\big(Qerror(Novelty\ Set)\big) \qquad \textbf{Eq. 3.2.1.10}$$

### 3.2.2 Generating a near-optimal performance benchmark

In any energy system, a reliable performance benchmark should provide information about the system optimal efficiency in any operation conditions. The conditions discretization issue is already tackled in the sections above but to find the optimal performance is a difficult approach either with data-driven or physical based methodologies. This delicate statement is the basis to attain a realistic system potential improvement capabilities and evaluate the current performance.

In most of the energy systems, as in refrigeration systems, the optimal performance is a complex measure to obtain due to the interrelation among various machines. The manufacturer information is only related with a single machine, obviating the influence of the various machines in the energy system, the physical modelling cannot contemplate the particularities and the complexity of a whole system and the data-driven techniques are limited to the historical scenarios. In the proposed methodology, such issue is approached searching the best historical performance curves of the system and generating new non-previously seen samples using the historical dataset, always within the specific MU that describe a fixed operation conditions.

#### *3.2.2.1 Best historical performance curves*

Performance curves of the system are highly influenced by the operation conditions, thereby, a benchmark under each identified MU is required. In this benchmark tailored within each MU, the historical performance curves can be really different due to the different machinery configurations. In industrial or huge residential refrigeration systems the compressors or the chillers, commonly allocated in parallel, operate simultaneously to provide the necessary cooling capacity. Thus, in such systems, each machine has different attrition, capacity and performance which affect the optimal operation. Furthermore, although the compressors should operate in nominal conditions to be efficient, the demand induce the machinery to operate in PLR conditions, where the performance decreases substantially.

This PLR term makes reference to the machine such as compressors or chillers which are working under their nominal capacity. Therefore, it is crucial to find out the best PLR configuration of each machine in order to supply the demand. Depending on the technology of the machine or the mechanism to modulate this PLR, the partial load efficiency curve changes significantly, **Fig 3.2.4** shows a common PLR-COP curve of a screw compressor [150].

Although the individual curves of each machine will be useful in the subsequent data proliferation section, the final objective is to obtain a cooling capacity-COP curve of the whole system, which is composed of various compressors as stated above. The $H_{COP}$ of the whole system is extracted from the samples that were identified in each MU as shown in **Fig 3.2.6** and it is made using the same strategy as the individual ones. Thus, a realistic benchmark is obtained as the method is fully based on historical data.

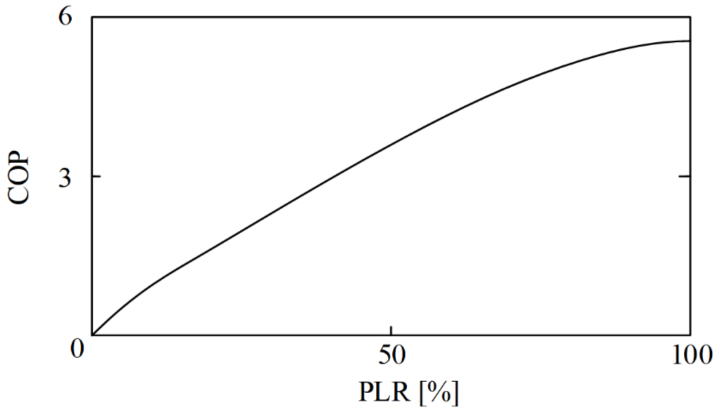


**Fig 3.2.4 - Illustration of a typical COP-PLR curve of a screw compressor.**

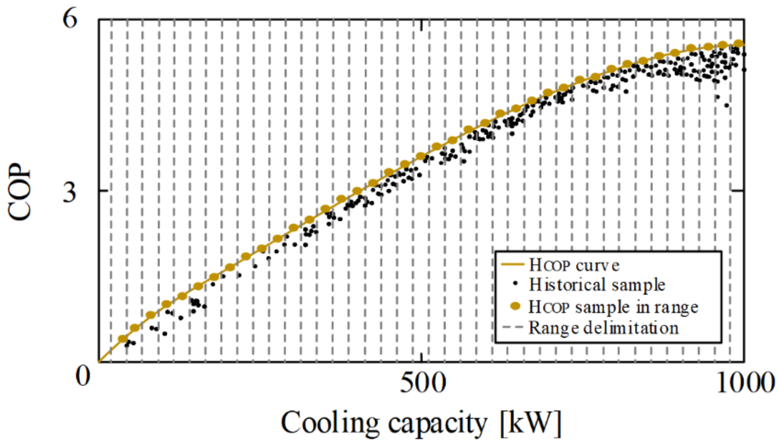


**Fig 3.2.5 – Illustration of a typical cooling capacity-COP curve of one compressor within a specific MU. Different COP ranges are divided using the vertical dashed lines.**

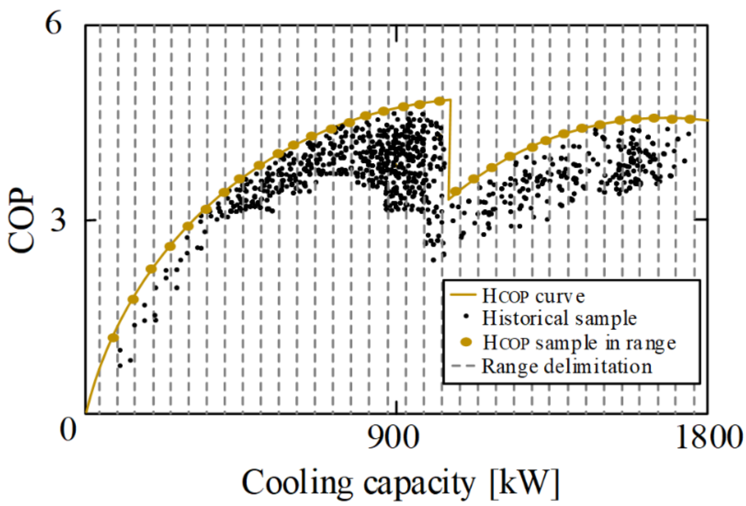


**Fig 3.2.6 - Illustration of a typical cooling capacity-COP curve of a MU with two compressors operating in parallel. The different sections in the curve rely on the situation when a compressor is switched on to supply higher a $Q$.**

### *3.2.2.2 Data proliferation*

The data proliferation is a technique presented by [79] which consists in the recombination of different historical samples to create new performance points. This methodology can be possible as the different compressors or chillers, under the same operation conditions, can be considered as linearly independent. Hence, a proliferation of the different machines cooling capacities, with its associated electrical consumption, can be done within the samples of each MU where the conditions are similar. However, with a high number of historical samples, the computational cost of the combinations increases rapidly being non-viable in most scenarios. To overcome such limitation, the samples under the optimal operation curve of each compressor or chiller, found in the previous step, are dismissed and only the best sample of its cooling capacity range is used. **Table 3.2.1** represents a reduced example of the proliferation implementation, where the best samples of each cooling capacity range are selected from each compressor to be afterwards combined. The first subscript of the cooling capacity and the electrical power refers to the compressor number whereas the second one define the sample number.

**Table 3.2.1 - Proliferation example of 4 samples of each compressor.**

| Compressor 1 best performance curve samples | | Compressor 2 best performance curve samples | | Proliferated samples | |
|---|---|---|---|---|---|
| **Electrical power** | **Cooling capacity** | **Electrical power** | **Cooling capacity** | **Electrical power** | **Cooling capacity** |
| $W_{11}$ | $Q_{11}$ | $W_{21}$ | $Q_{21}$ | $W_{11} + W_{21}$ | $Q_{11} + Q_{21}$ |
| $W_{12}$ | $Q_{12}$ | $W_{22}$ | $Q_{22}$ | $W_{12} + W_{21}$ | $Q_{12} + Q_{21}$ |
| $W_{13}$ | $Q_{13}$ | $W_{23}$ | $Q_{23}$ | $W_{13} + W_{21}$ | $Q_{13} + Q_{21}$ |
| $W_{14}$ | $Q_{14}$ | $W_{24}$ | $Q_{24}$ | $W_{14} + W_{21}$ | $Q_{14} + Q_{21}$ |
| | | | | $W_{11} + W_{22}$ | $Q_{11} + Q_{22}$ |
| | | | | $W_{12} + W_{22}$ | $Q_{12} + Q_{22}$ |
| | | | | $W_{13} + W_{22}$ | $Q_{13} + Q_{22}$ |
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| | | | | $W_{12} + W_{24}$ | $Q_{12} + Q_{24}$ |
| | | | | $W_{13} + W_{24}$ | $Q_{13} + Q_{24}$ |
| | | | | $W_{14} + W_{24}$ | $Q_{14} + Q_{24}$ |

With all the artificially created samples, the COP is calculated and used along with the historical ones to create the near-optimal cooling capacity-COP curve within each MU. Thanks to these artificial scenarios created with the data proliferation, new performance boundaries never seen before in the historical dataset can be found, overcoming the historical control rules that limit the operation situations. **Fig 3.2.7** shows how from the $H_{COP}$curves from each compressor, C1 and C2, the new data points are created, depicted in green. Using the same range partition strategy as employed with the historical data, a new upper boundary of COP can be found ($B_{COP}$), combining the $H_{COP}$ and the best proliferated COP ($BP_{COP}$) data, obtaining thus a more reliable benchmark in each MU. Note that the proliferated samples overcome the historical ones in situations where more than one compressor is needed, while in scenarios where the demand can be supplied with one compressor, the best performance is always achieved employing only one machine. Such appreciation also indicates that the compressors configuration in parallel operation used in the historical database can be improved in order to increase the system efficiency.

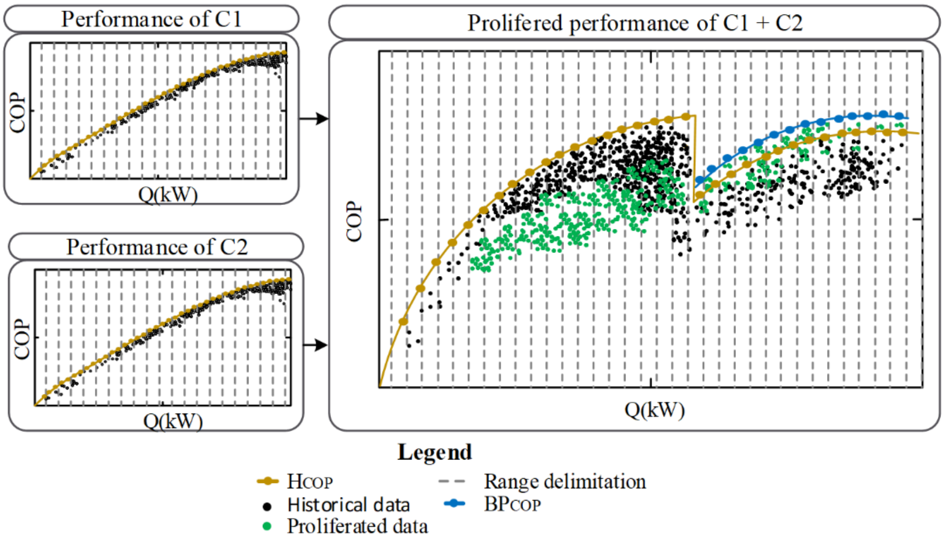



**Fig 3.2.7 - Example of $Q$-COP curve creation with proliferated data of a single MU. The operation combinations of compressor1 (C1) and compressor2 (C2) lead to a better COP scenarios in some $Q$ ranges.**

### 3.2.3 New data assessment

The aim of the performance assessment is to evaluate new samples, such samples can be historical data, to analyse past system behaviours in a forensic way, or online data, acquired in real-time from the system. In both scenarios such new data has to be evaluated in regard the benchmark in order to compare the desired sample with its near-optimal performance operation reference.

#### *3.2.3.1 Benchmark evaluation*

First of all, with the new samples, the same preprocessing as in the operation discretization step is performed. Such process consists in eliminate the samples that contain any measurement error. Even though such samples can be also identified by the posterior uncertainty evaluation step, this preprocessing is maintained to avoid erroneous acquired measurements. While the main objective of the subsequent uncertainty evaluation, as previously mentioned, is to detect samples that are not common in the system operation and hence, it is a signal that the system is deviating from its usual operation and the performed comparison is not trustworthy. Furthermore, in the scenario that the new data evaluated comes from the real-time operation, this preprocessing step is not time consuming and do not compromise the methodology performance.

Subsequently, this new data is mapped to the benchmark. Such operation consists in assigning the new sample to a certain discretized area, described by a MU. In this case the selected MU is the BMU, the nearest neuron of the evaluated sample, since it is the area that better describes its operation conditions. Therefore, the new sample can be compared with the near-optimal performance curve described by its BMU, shown in **Fig 3.2.8**.

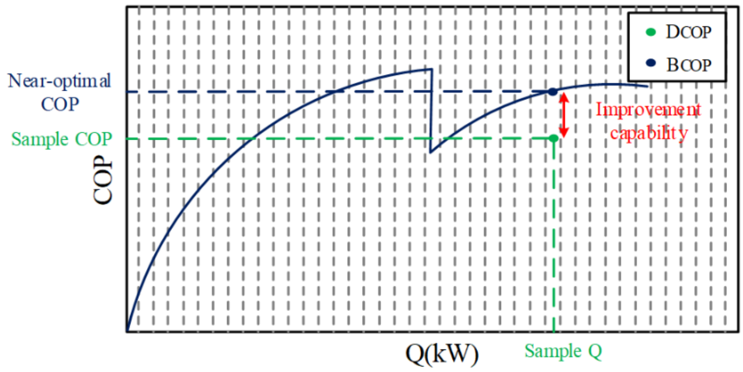



**Fig 3.2.8 –Example of a sample performance comparison. Near-optimal COP curve of its BMU from the benchmark versus the analysed sample COP. Both considering the cooling capacity.**

### *3.2.3.2 Uncertainty evaluation*

In this step, the new sample already evaluated with the benchmark, is labelled according the previously created uncertainty thresholds. Such operation is done employing the distance between the evaluated sample and its BMU, as explained in the Section 3.2.1.3. A higher distance means that the sample operation conditions are not well represented by its BMU and hence, the comparison is not trustworthy. Such information also indicates that the system is operating in different conditions than usual, which can reveal some kind of malfunction.

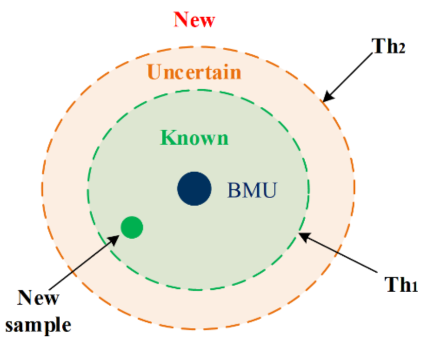



**Fig 3.2.9 – Illustration of a new sample in regard to its BMU and the uncertainty thresholds.**

## 3.3 Experimental results

The performance assessment is approached taking into account the compressors operating in parallel of the refrigeration system due to its huge energy expenditure explained in previous sections.

### 3.3.1 Training and configuration of the methodology

#### *3.3.1.1 Data Preprocessing*

First, the available historical data from the database is analysed with, at least, the operation measurements of one year. The length of one year is preferred because the operation modes of the refrigeration system are normally cyclical each year, which means that the performance is very dependent on the outside temperature.

Despite the vast amount of variables involved in the refrigeration process, to discretize the operation space only the variables that affect the compressor performance are selected [151]: the suction or evaporation pressure and the discharge or condenser pressure. Although the cited study [151] makes reference to the temperatures, the proposed methodology use pressures, which are easily extracted, due to the instrumentation available in the case study. Afterwards, the DB is filtered to eliminate periods of time where the system is not working and periods of time where some measurements are incorrectly stored due to registered sensor failures. Additionally, all the measurements are scaled from 0 to 1 for generalization purposes in order to apply posterior data-driven algorithms.

To create the performance assessment benchmark, part of the historical data is used. Specifically, 3 every 4 weeks are selected to train the model and the remaining weeks are used to simulate real operation conditions to attain a balanced distribution among the different dataset scenarios.

#### *3.3.1.2 Outlier detection*

First of all, the data from the training set is selected and the MVKDE is employed as an outlier or anomaly filter to divide the training set in the normal set and the novelty set as explained in the above section. For the training procedure, the MVKDE is configured with a multiplicative function, a Gaussian kernel and the bandwidths are set through least squares cross-validation. With such configuration, 90% of the data is labelled as normal and 10% as novelty. The dataset splitting results are shown in **Fig 3.3.1**, as it can be appreciate most of the data is concentred in mainly two areas.

a)

b)

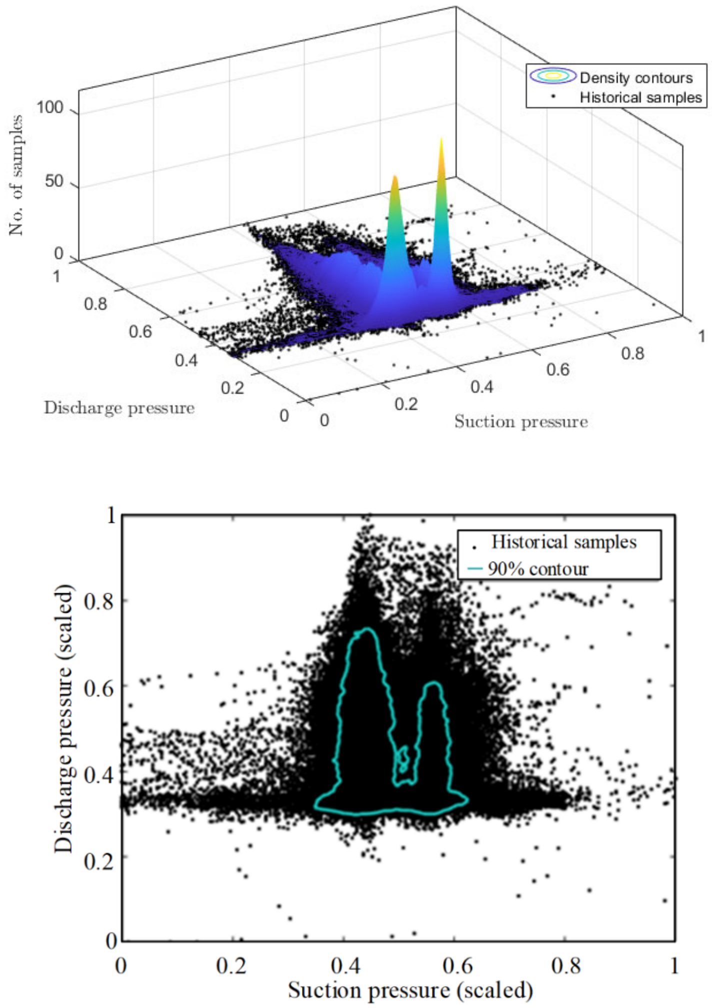



**Fig 3.3.1 - MVKDE of the data. a) Samples density. b) Splitting contour.**

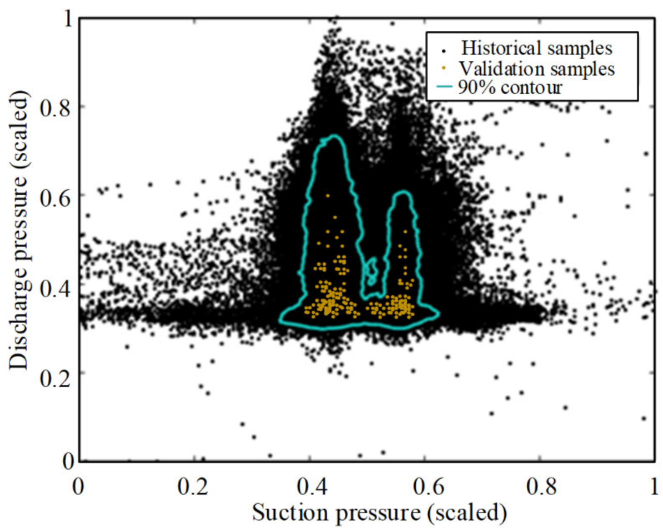



**Fig 3.3.2 - Normal operation data validation.**

The system experts impute the two clearly defined density zones to the main operation modes as the system changes its suction pressure set points depending on the requirements of the spaces to refrigerate. Furthermore, to ensure the capability detecting anomalies of the MVKDE, a validation set previously labelled by a system expert is used. The method is able to identify the 100% of samples labelled as normal, **Fig 3.3.2**, affirming the uncertainty detection effectiveness.

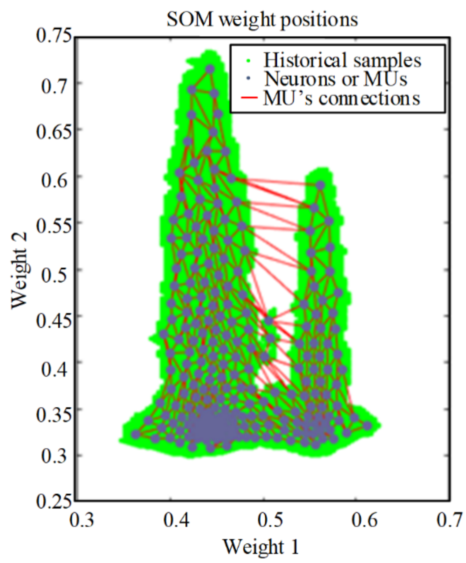
### *3.3.1.3 Operation characterization*

Once the normal set and novel set are obtained, the SOM training is performed employing only the normal set. For the SOM configuration, a hexagonal grid type connection is selected, a planar map type, a Gaussian neighbourhood function and a 15x15 output grid, which means a total of 225 neurons.

Different configurations were tested, nevertheless the aforementioned configuration presented the minimum number of neurons with no-hits without compromising the characterization resolution. Furthermore, a low mean *Qerror* without overfitting the network to the distribution is achieved, specifically a value of 0.02 is obtained. This SOM configuration is highly dependent on the dimensions number of the dataset and the data distribution, there is not a specific rule to achieve the best possible parametrization.

The normal set used to train the SOM and the resulting grid distribution is shown in **Fig 3.3.3 a)**. The neurons distribution covers the whole input data space allocating more neurons on denser areas to obtain more resolution. On the other hand, **Fig 3.3.3 b)** shows the U-matrix which represents the 2D output grid of neurons with the distances between the adjacent neurons coloured with a darker colours when the distances are larger.

a)



b)

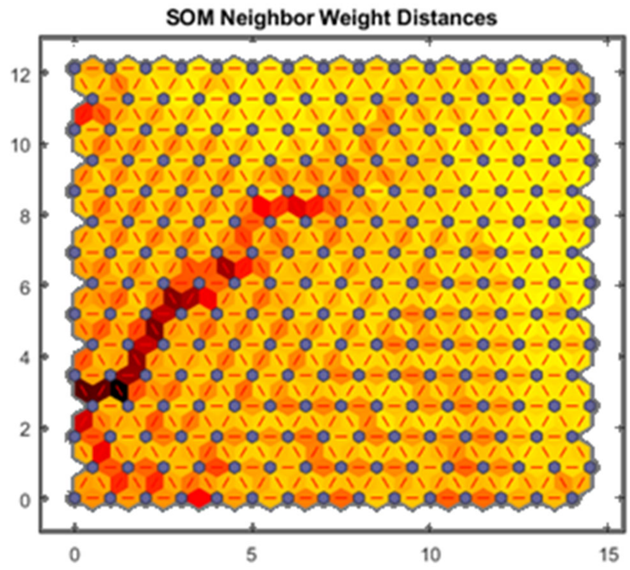
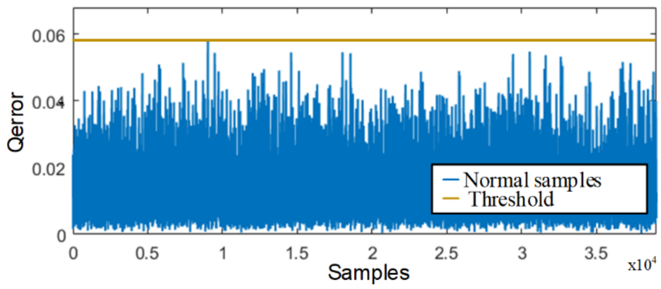



**Fig 3.3.3 - SOM plots. a) Neurons distribution in the input space. b) Output 2D grid: U-matrix.**

### *3.3.1.4 Uncertainty delimitation*

Thus, a 2D grid of neurons or MUs discretizing all the operation space of the system is obtained. At this step, the methodology is able to map any new sample to the created grid, which corresponds to a similar operation conditions. Nevertheless, to ensure that the BMU of each new sample to evaluate is representative enough, the uncertainty thresholds are created.

a)




b)

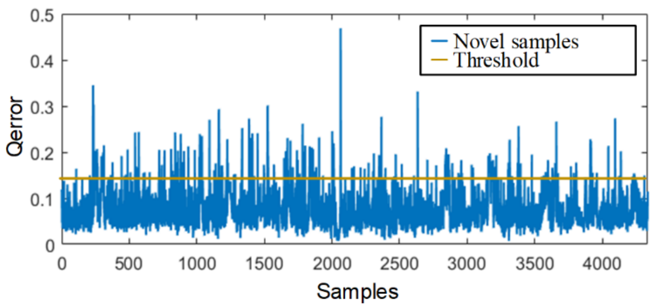



**Fig 3.3.4 - *Qerror* thresholds. a) *Th1*. b) *Th2*.**

The first threshold, $Th_1$, for the uncertainty analysis is obtained according to **Eq. 3.2.1.9**. Then, the novel set is evaluated by the trained SOM and the second threshold, $Th_2$, is obtained according to **Eq. 3.2.1.10**. The values are 0.058 and 0.15 respectively. In **Fig 3.3.4** the *Qerror* of the normal set and the novel set are shown as well as the uncertainty thresholds $Th_1$ and $Th_2$.

### *3.3.1.5 Near-optimal performance benchmark*

With the robustness measures already applied, the next step is to create the performance benchmark of each MU. For this purpose, the best historical performance of each compressor and of the whole system is found. To attain such goal, the signals of the cooling capacity and electrical power consumption of each machine are used and the Cooling capacity-COP curves are calculated within each MU, selecting the cooling capacity ranges of 20kW each one. Finally, the last step is to proliferate the historical data from both machines to obtain the performance curve benchmark in each MU, employing the strategy explained in the previous section. **Fig 3.3.5** depicts a part of the whole 15x15 grid of MUs with its cooling capacity-COP curves. The illustration is only a demonstration of the final performance assessment grid and is not from the entire lattice due to the dimensions of the image required to depict it entirely.

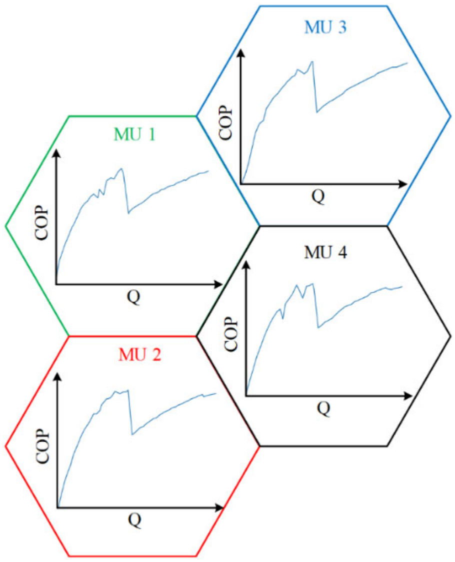



**Fig 3.3.5 - Part of the 15x15 grid of MUs with its best performance curves. Each MU specifies a discretized area with its suction and discharge pressure values.**

In the whole performance grid, it is appreciable that each MU has its own performance curve. Due to the SOM topological preserving properties, nearby MUs between them have slight different performance curves, while the difference in MUs from distant regions of the grid is higher as the operation conditions are significantly different. Such difference is observable in **Fig 3.3.6** where the performances curves of two distant neurons are depicted. As it can be appreciated, the maximum cooling capacity achievable in both scenarios is reasonably different and it is also noticeable that the maximum COP that can be reached is really different. In addition, the switch, which is the situation where the second compressor is needed to continue increasing the $Q$, is also visibly different. Such significant variations appear even though the machinery of the system is always the same, which means that the changes are caused by the different operation conditions.

Such differences among the different performance curves of the created benchmark endorse the necessity to assess the refrigeration system taking into account the different conditions. Otherwise, the assessment would not be trustworthy.

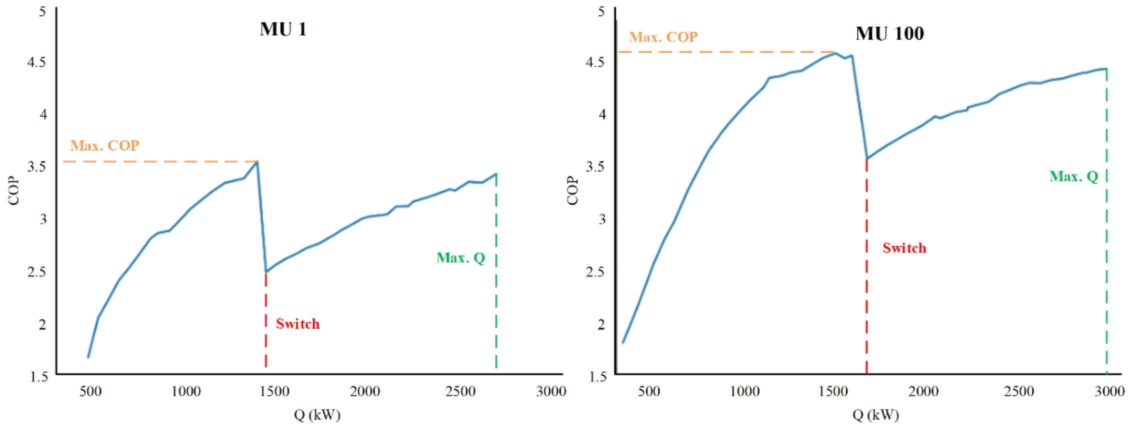



**Fig 3.3.6 – Example to depict the significant difference between the performance curves of two distant MUs.**

### 3.3.2 Evaluation of the method in the refrigeration system

The performance assessment tool, at this stage, is ready to evaluate new samples and measure the compressors efficiency. The test set, separated at the beginning of this experimental study, is used to validate the results. First of all, the aforementioned preprocessing is performed and the normalization is done considering the maximum and minimum values obtained from the variables on the training set. Subsequently, this preprocessed test dataset of the refrigeration system is mapped to the grid and its COP ($D_{COP}$) is compared against the benchmark COP ($B_{COP}$) as shown in **Fig 3.3.7**. It is illustrated that the compressors configuration still has room for improvement in order to achieve the proposed benchmark performance.

This performance evaluation depicted in **Fig 3.3.7** contains all the steps specified in the benchmark creation section. Therefore, the assessment takes into account several aspects such as the various variables that affect the performance, the uncertainty of the input data and the capability to overcome the historical scenarios with the proliferation.

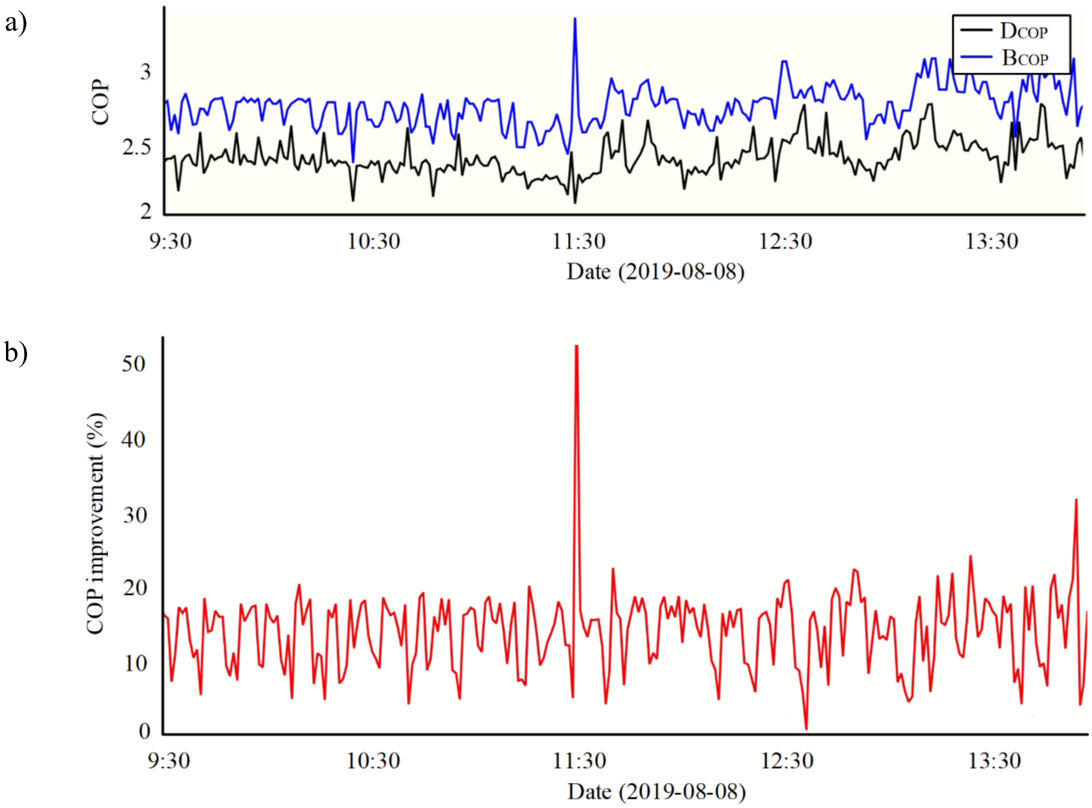



**Fig 3.3.7 - Detail of the test data assessment. a) Performance obtained in the test data versus the benchmark reference. b) Improvement capabilities of the compressors efficiency.**

In this regard, the performance enhancement capabilities according to the assessment are about 15% of COP. It should be noticed that in a regular operation it is not always possible to reach the complete improvement and operate in the benchmark COP conditions. The variability of the discretization algorithm and the non-registered variables such as incidences or the compressors mechanical condition which varies in time cannot be considered by the algorithm. Nevertheless, a substantial part of such improvement can be achieved if the compressors are managed in an optimal way according to the system conditions and the demand trend requirements. Chapter 4 of this thesis will explore such solutions.

### *3.3.2.1 Advantages of space discretization with multiple variables*

One key aspect of the methodology is to consider process operation variables to provide a reliable assessment of the current COP. In this regard, the discretization of the operation space is made to be able to compare the COP under the same operation conditions and thus avoid non-reliable results. To contrast the assessment with the scenario in which the operation variables are not contemplated, a comparison of the expected optimal COP ($S_{COP}$) if the environmental variables were not used and the proposed method is performed and depicted in **Fig 3.3.8**. The $S_{COP}$ is calculated obtaining the best COP for specific cooling capacity necessities, without the use of any other variable.

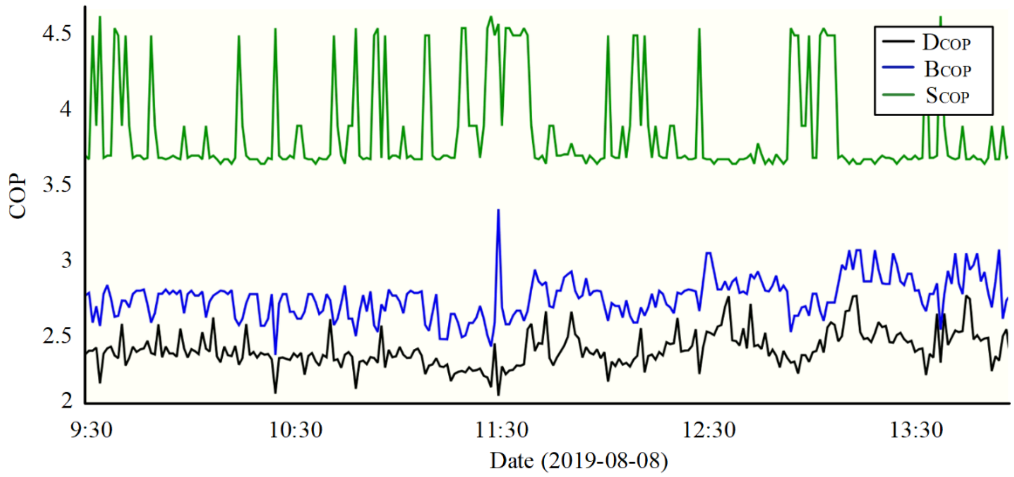



**Fig 3.3.8 - Detail of the test dataset with the proposed COP benchmark and the simple COP expectations without taking into account the operation variables.**

As it can be seen, the performance without taking into account the operation variables is much higher and cannot be reached according to system experts providing unrealistic improvement capabilities.

However, the discussion of the benefits of including system condition in the assessment of the performance is related with the system behaviour dynamics. In this regard, the modelling of industrial systems is a complex task, as it has been explained in Chapter 2, the mathematical modelling of such systems is a challenging task due to the cross-relation of all the different elements affecting the system.

As can also be seen in the figure, the evaluation of the COP without any information from the variables that affect its operation gives a simple pattern with a mean $S_{COP}$ of 3.8 that do not follow the dynamics of the system. This simple pattern is almost conformed by two different states, the higher and the lower, the higher $S_{COPs}$ are attributed to situations where only one compressor is working and the lower $S_{COPs}$ are attributed to situations where two compressors are operating in parallel.

Such constant states indicate that the evaluation algorithm is not adapted to the system dynamics of variation. However, as can be seen in the figure, the response of the proposed methodology, $B_{COP,}$ follows the frequency of variation of the current $D_{COP}$ of the system, which is the intrinsic frequency of the dynamics of the system. In this regard, it can be established that adding, in a proper way, the information of the system is an indirect way of modelling the dynamics of its behaviour.

### 3.3.2.2 *Assessment robustness with uncertainty delimitation*

To provide a reliable and qualitative value of the performance, each sample of the test set is mapped to the grid and labelled according to the thresholds previously obtained with the uncertainty detection methodology, into known, uncertain and new. This labelling provides robustness to the assessing and avoid non trustworthy measurements which can lead to incorrect maintenance or improvement strategies. **Fig 3.3.9** illustrates the labelling obtained from the same part of the test dataset as the previous figures.

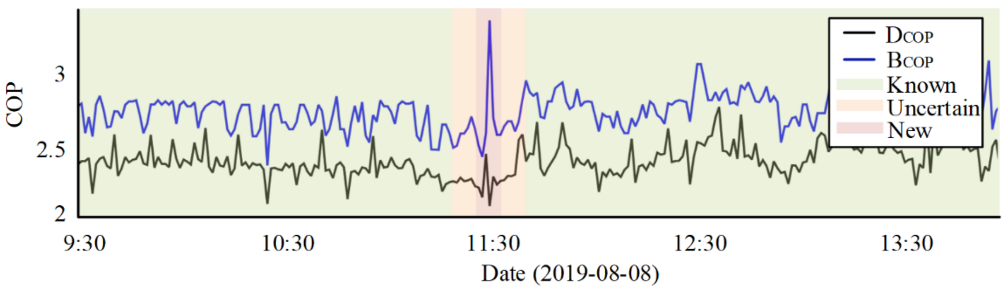



**Fig 3.3.9 - Detail of the test data with the uncertainty labelling coloured.**

It is noticeable that during the performance spike around the 11:30, the improvement capabilities increment disproportionately. That happened because the suction pressure decreased abruptly leading the system in non-representative operation conditions. In such situation, the assessment methodology is capable to detect the anomaly working operations and inform that the assessment is not reliable due to the lack of data around these conditions.

This characteristic of the methodology is of a critical significance in real industrial monitoring systems. In this regard, the proposed methodology is in charge of controlling the degree of knowledge that it has for every evaluated sample of the system. As each sample is calculated considering the current system condition, this uncertainty evaluation can be used to detect punctual abnormal operation as can be seen in the figure, but it also allows to push the monitoring methodologies to new horizons when a persistent not-known operation is given. In this situation, the method can efficiently detect such operations and report them in order to seek the origin of such new behaviour not seen in the historical database. This capability makes possible to act in consequence against this new behaviour, to see if this new situation is a desirable condition, or in the other hand, presents an operating problem that must be corrected by the operators of the system.

### 3.3.2.3 *Discretized proliferation benefits*

Finally, each $B_{COP}$ curve of each discretized area of the operation space, MU, is obtained applying the proliferation technique. Such algorithm allows to attain better possible configurations than in the historical dataset. To evaluate the improvement of the proliferation in regard to the best historical COP ($H_{COP}$) in the specified operation conditions delimited by each MU a comparison is made, depicted in **Fig 3.3.10**.

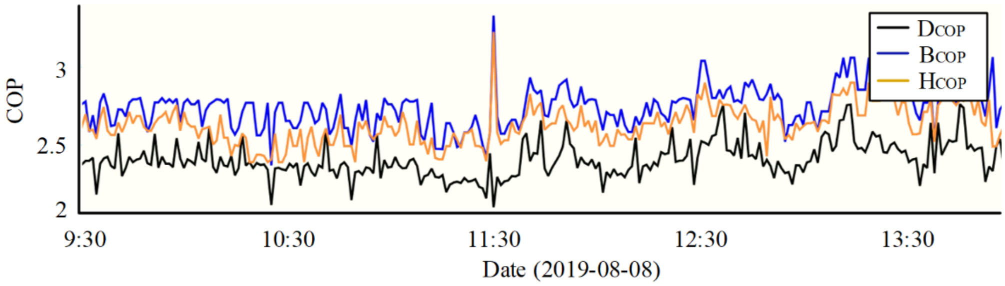



**Fig 3.3.10 – Detail of the test data performance with the proposed benchmark and the historical best COP under the specific operation conditions.**

It is appreciable that the proposed benchmark COP overcomes the best historical scenarios which are constrained with the current control strategy. These differences are due to the different compressors configuration obtained with the proliferation do not happen in the real scenario due to the current compressors control strategy. This proliferated benchmark overcome by around 3% of COP improvement regarding the historical one.

This capability of increasing historical performance is a critical aspect in every data-driven methodology, and with this methodology, the evaluation limits are pushed into situations never seen on the historical database to evaluate the true potential of improvement. Furthermore, such potential can also be beneficial in the optimization strategies creation, a topic which is further explored later in this thesis. In this regard, Chapter 4 deals with how to develop a methodology able to recommend near-optimal set points for the compressors. Such methodology takes advantage of this benchmark able to consider performances beyond the historical database, allowing new compressors configurations to reach performances found in the proliferated samples.

## 3.4 Conclusions and discussion

The proposed performance evaluation methodology takes advantage of the data acquired from the refrigeration system to avoid the physical based approaches deficiencies. The strategy obtains a near-optimal performance benchmark taking into account the process variability and the multiple factors that limit the operation efficiency. Moreover, with the data proliferation strategy applied in each operation area, new scenarios are created artificially which can contribute to the improvement of the benchmark and to overcome some of the limitations of the data-driven approaches. Thus, a realistic potential energy savings can be estimated since the benchmark is developed using real system data in comparison to classical approaches which are based on ideal conditions. This efficiency evaluation tool can be used as a benchmark to assess new data acquired in real-time from the refrigeration system or to perform a forensic assessment employing historical datasets. Furthermore, the methodology is able to discriminate the uncertainties of the samples in order to provide a robust evaluation. Therefore, it can be used to compare different compressors control strategies, identify abnormal behaviours and quantify the potential operation improvement in a robust manner.

In order to validate the method, data from a real refrigeration system is evaluated. The results demonstrate that the outlier detection, uncertainty thresholds, and the development of the discretization characterization technique, fit the system operation space to provide an accurate assessment of the performance. With the performed validations, is observed that the studied system has room for improvement varying the compressors control strategy and, in addition, the methodology provides the possibility to detect possible faults or abnormal operations thanks to the uncertainty labelling.

# 4.

## Operation improvement: set point recommendation

In this chapter the proposed methodology to recommend near-optimal PLR set points is presented. Such methodology is based on historical data and considers scenarios where two compressors are operating in parallel and situations where a switch is necessary. Robustness and stability concerns are also tackled.

CONTENTS:

# 4 Operation improvement: set point recommendation

The present chapter takes advantage of the performance assessment benchmark previously created in order to obtain a reliable set point recommendation. The methodology employs the proliferated data and a demand trend classification to suggest an efficient operation set point. The study is detailed in the subsequent sections and tested under the real case study system.

## 4.1 Introduction

This section outlines the background and motivation for this particular research topic and the description of the innovative contributions of the presented methodology.

### 4.1.1 Background and motivation

Systems composed of various machines are often difficult to manage in an efficient manner due to the multiple factors that affect its operation. In most scenarios, changes in set points of the operating machinery can lead to a reduction of the energy expenditure maintaining the demand requisites, however, it is not straightforward to find the ideal recommendations. In addition, a trade-off among the individual machine optimal operation and the whole system efficiency is commonly faced. The state of the art, presented in the Chapter 2, enumerate different approaches to tackle such issues but conclude that more research is needed in order to develop a data-driven technique fully applicable in a real industry.

Specifically, as stated before in the performance assessment, in large overfeed vapour compression systems various compressors operate in parallel to supply the cooling demand. In this regard, their performance curves are highly affected by different factors enumerated in the previous chapter. In such topic, this problem is also named in literature as the optimal partial load ratio, PLR problem, which makes reference to the amount of cooling capacity that each machine has to provide to fulfil the demand necessities with the minimum energy expenditure.

Supply this required amount of cooling capacity in an efficient way in order to preserve the refrigerated spaces under the desired conditions is a challenging project. Moreover, the continuously varying load associated with industrial refrigeration processes and its direct relationship with the product quality, produce a scenario where the compressors are constantly varying its capacity with few steady state situations. Thus, there is not option to adapt the classical model-optimization approach due to the computation time limitations. Furthermore, to make operation recommendations based on a physical or data-driven model can affect the system stability due to the errors and uncertainties of the models, fact that is not permissible in industrial refrigeration.

These specific refrigeration constraints, where a slightly variation in the operation conditions provoke an important performance variation, along with the current state of the art shortcomings, create a perfect environment to perform a deeper research in the data-driven set point recommendation strategies. A robust and reliable methodology should be developed in order to satisfy the industrial refrigeration systems necessities, where various compressors are allocated in parallel and the load and the operation variables are constantly changing.

### 4.1.2 Innovative contribution

The presented method to approach the PLR recommendation of industrial compressors is purely based on historical data. Hence, some of the modelling concerns regarding the physical based techniques incapacity to represent the system behaviours in a trustworthy manner are avoided. However, data-driven strategies also present drawbacks such as the lack of generalization capabilities and the restrictions with the historical operations. Since the proposed methodology is grounded on the previous performance benchmark, and such approach already contemplates the limitations of this data-driven methods, the proposed solution is capable to deal with this shortcomings taking advantage of the uncertainty detection, space discretization and proliferation techniques.

On the other hand, independently of the modelling processes, the common recommendation techniques are based on optimization algorithms or IF-THEN rules. The classical optimization approaches overcome the IF-THEN rules results regarding the energy efficiency tests, but are not suitable in industrial situations such as the case study due to its computational burden. Therefore, the proposed methodology suggests near-optimal and reliable set points without the contribution of an expert to create the rules or a time costly optimization solution.

To perform such task, the ideal performance curves of the previously explained assessment methodology are substituted with the ideal PLR of each compressor, obtaining thus, an artificially created operation recommendation taking advantage of the compressors operation proliferation. This recommendation is done regarding its specific operation conditions of the grid and can be even better than the historical functioning. The generation of such PLR curves is grounded on the benchmark COP curves of the Chapter 3. In this case, the PLR values of such benchmark samples, that were able to achieve the near-optimal COP, are used to perform the PLR curves.

*A **fast set point recommendation methodology** should be able to obtain **near optimal PLRs** using only historical data and **considering the system operation conditions**.*

With the explained innovations of the methodology, a trustworthy and fast set point recommendation is obtained with a great precision about its operation conditions and capabilities.

However, even though the discretized area of the grid should represent the operation conditions of the system, a neighbourhood function is applied to mitigate the slight differences among the reference neuron and the real conditions. Thus, a more precise set point recommendation can be suggested as the PLR is found using also the neighbours' conditions, which also helps to generalize the solution and smooth the transitions between recommendations.

Moreover, the recommendations should guarantee the constraints in regard to the refrigerant temperature. Without this restriction, the products cannot be refrigerated as needed. This entails the necessity to modify the cooling capacity in order to preserve the refrigerant temperature requisites.

Finally, in order to provide a safe recommendation in boundary situations where the recommendation changes the number of switched machines, a demand trend classification is developed in order to evaluate the change necessity and minimize the starts and stops of the compressors. Such situations can be harmful for the compressors remaining useful life and reduce its efficiency.

*The recommended **set points** should **take into account consumption trends** and **preserve the system constraints** in order to guarantee **efficient and safe recommendations** to the compressors.*

In conclusion, a novel data-driven method that avoids the time consuming optimization stage, overcomes historical scenarios, takes into account the demand trend and provides a reliable PLR recommendation is presented.

## 4.2 Set point recommendation methodology

This set point recommendation methodology is based on the previously created performance grid in order to recommend near-optimal PLR curves within each operation condition. The methodology recommends the PLR set points to supply the required cooling capacity while ensuring a reduction in the electrical energy expenditure. **Fig 4.2.1** illustrates the designed steps to perform the recommendation method, which is composed by two main parts: the PLR curves generation and the set point recommendation.

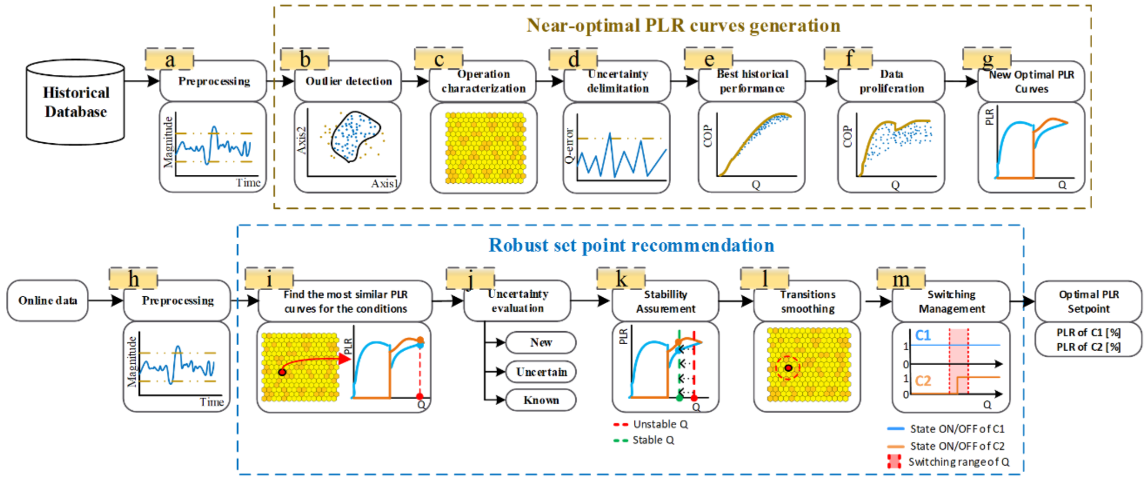



**Fig 4.2.1 – Set point recommendation methodology overview. Note that the diagram illustrates the example case in which two compressors, C1 and C2, are used to supply the cooling demand.**

As mentioned before, the generation of the PLR curves is grounded with the previously created assessment benchmark, steps (a)-(f), extensively explained in Chapter 3. Therefore, in this set point recommendation scenario, the purpose is to translate the COP curves of the assessment benchmark to PLR curves, step (g). For this reason, the compressors PLR configurations associated to the benchmark COP are selected to generate these near-optimal PLR curves.

Firstly, and utilizing the historical database, the methodology generates a near-optimal PLR curves grid considering the operation conditions. However, the application of these PLR set point recommendations in a real-time industrial scenario may produce instability issues. Therefore, the main efforts of this methodology are applied to generate a robust set point recommendation in a real-time scenario.

This robust set point recommendation starts with the acquisition of a new sample in real-time. In (h), the same preprocessing as in the PLR grid generation is applied, detailed in Chapter 3. In this scenario, where the robustness of the recommendation is fundamental to guarantee the product requisites and the machinery safety, samples that do not pass the preprocessing constraints are dismissed in order to avoid a system destabilization. In such situation, the methodology does not make any modification on the recommendation and waits till the next sample. If the situation persists, and due to the impossibility to ensure the required robustness, the methodology propose to deactivate the new management, giving way to the previous management strategy.

Subsequently, the new sample, already scaled thanks to the preprocessing step, is mapped to the PLR grid in order to find its representative neuron according to its operation conditions, (i). Thus, the near-optimal PLR curves for its particular operation conditions are obtained. As in the performance assessment, the new sample can be significantly different from any neuron of the grid, meaning that the system is operating in novel or uncertain conditions, (j). In this case, that rarely should happen but possible, the recommendation system does not make any modification on the recommendation and the same strategy as in the preprocessing step is employed.

At this point, some of the aforementioned stability issues arise. The first one is regarding the cooling capacity. As the cooling load has a dynamic behaviour and is constantly changing, the required $Q$ to maintain the refrigerant temperature in the desired values should change as well. In such scenario, the current cooling capacity provided has to be modified in order to preserve the refrigerant temperature within the desired boundaries. This modulation of the $Q$ value, step (k), is done considering the refrigerant temperature error, measured with the suction pressure error.

The second stability issue is associated with the intrinsic characteristics of a discretized model. Even though the neurons describe accurately the space that represent, the transition between them can produce an undesired abrupt change in the PLR set point. Therefore, to smooth the transition among different neurons and to represent in a more accurately way the current operation conditions, a smoothing strategy is developed. Such smoothing, (l), is developed considering the neighbour neurons, and giving to them a weighted contribution, depending on its distance, in the final PLR set point.

At this stage of the methodology, a near-optimal set point considering the neurons transition and the refrigerant temperature is already obtained. Nevertheless, the regular operation of a refrigeration system with more than one operating compressors may lead to situations in which the same demand could be supplied with one or more compressors. The usage of two compressors in scenarios where only one is needed should be minimized as it is extremely inefficient and destabilize the system during a certain period of time since the compressor switching action. In this regard, this switch of the compressors can also affect negatively the stability and the efficiency of the system, as well as the compressors health.

Therefore, step (m) deals with the problem of how to avoid unnecessary switch on/off actions. This step introduces a demand trend classification method to identify future trends of the cooling capacity in order to assure an optimal decision of switching the current number of compressors.

Finally, the output of the proposed operation optimization methodology contains a robust near-optimal PLR set points of each compressor of the refrigeration system. In this regard, the following sections cover the detailed explanation of the steps (g)-(m) defined before. As aforementioned, this methodology is grounded with the performance assessment, hence, the details of steps (a)-(f) are explained in Chapter 3.

### 4.2.1 Generating near-optimal PLR curves

Compressors are machines that below its nominal conditions are really inefficient as demonstrated in Chapter 3. The partial load that reduces its efficiency and its performance is highly affected by various operation variables as well. Hence, it is of vital importance to manage the PLR of the compressors in scenarios where multiple compressors should operate in parallel.

Such PLRs should guarantee a near-optimal compressors configuration to attain the desired $Q$. Thus, it is necessary to create PLR curves under different operation conditions to be able to recommend the best configuration regardless the variables that affect their performance. Furthermore, such PLRs should not be conditioned by the historical operation configuration, therefore, it is mandatory to create new non-previously seen scenarios to overcome the bias induced by the historical control.

In the proposed methodology, such concerns are managed applying the same strategy as in the performance assessment. All the variables that affect the compressors performance are taken into account as well as the capability to create new artificial samples. Due to the most of these topics are detailed in Chapter 3, only the step (g) of the **Fig 4.2.1** is explained in this chapter.

#### *4.2.1.1 Near-optimal PLR curves generation*

This step is grounded on the benchmark COP curves generated in the performance assessment methodology. Those curves, were generated discretizing the cooling capacity of each neuron of the grid in various ranges and selecting the best COP sample in each range. Hence, each selected sample contains the best achievable performance under that specific conditions. Thus, the near-optimal PLR curves are extracted copying the PLR configurations of such benchmark performances. An example of the transformation is depicted in **Fig 4.2.2**.

In this manner, the resulting multi-dimensional grid is able to recommend a near-optimal PLR for a defined set of system conditions. Set points that are truly achievable as are based on the historical operation and its proliferation. Thus, each MU contains a near-optimal curve that relates the cooling capacity required by the system in such operation, with the new near-optimal PLR of the compressors.

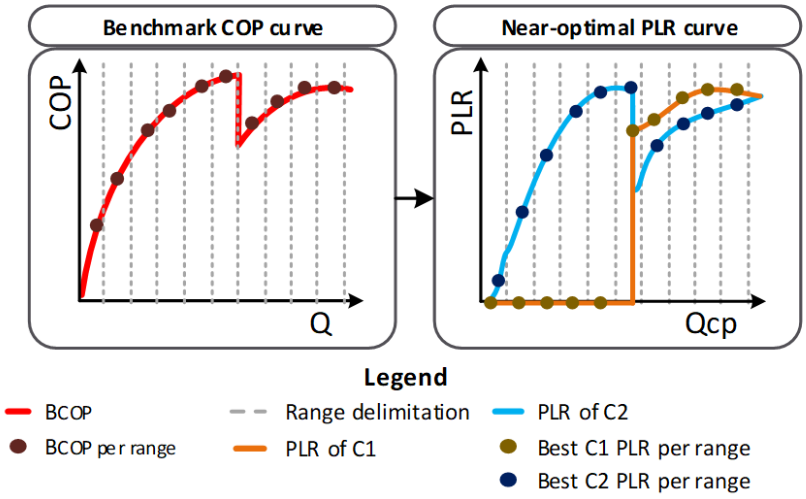



**Fig 4.2.2 – Passing from COP curves to PLR curves. Illustration of a specific MU.**

### 4.2.2 Dealing with PLR recommendations in industrial refrigeration systems

Even though the near-optimal PLR curves are already created, it is not straightforward to recommend the set points obtained from the curves to the industrial refrigeration system in real-time. The robustness of such recommendations must be guaranteed.

In this regard, the PLR recommendations should not only provide the most efficient compressors PLR to cover the cooling necessities, also have to ensure the safety of the machinery and the quality of the final product. For this reasons, the methodology should avoid abrupt changes in the set points, should reduce unnecessary compressors switchings and should ensure a specific refrigerant temperature. These three aforementioned issues are tackled in the subsequent sections.

Notice that the steps (h)-(j) of **Fig 4.2.1** are not explained. Such steps are detailed in Section 3.2.3 of the performance assessment methodology presenting only two differences in this set point recommendation. Firstly, in this case the COP curves are replaced by the previously generated PLR curves. And secondly, in this case the preprocessing and uncertainty steps are used to dismiss PLR recommendations to avoid damaging the products and the machinery.

#### *4.2.2.1 Ensuring the refrigerant temperature stability*

As explained above, the behaviour of the refrigeration system requires the control of the suction pressure to maintain the refrigerant temperature in a safe range. Therefore, in step (k) of **Fig 4.2.1**, a strategy to approach this concern is presented. The strategy consists in a shifting procedure of the $Q$ at each iteration. This shifting is carried out according to the suction pressure deviation from its desired value. The shifting of the $Q$ values allows to change the PLR of the compressors and assure the stability of the process. The proposal to shift the $Q$ demand is performed according to a polynomial function, presented in **Eq. 4.2.2.1**, that relates the allowed pressure error with the desired correction. This correction is adjusted in regard to the dynamics of the system.

$$Q^* = Q + \varepsilon_p \times R \qquad \text{Eq. 4.2.2.1}$$

Where $Q^*$ is the corrected cooling capacity, $Q$ makes reference to the current cooling capacity, $R$ is the correction ratio and $\varepsilon_p$ corresponds to the pressure error, shown in **Eq. 4.2.2.2**,

$$\varepsilon_p = \frac{(sp - spSP)}{sp} \qquad \text{Eq. 4.2.2.2}$$

where $sp$ is the current suction pressure and $spSP$ is the suction pressure set point.

### *4.2.2.2 Neurons transition smoothing*

Another important aspect to ensure the stability and avoid abrupt changes in the machinery behaviour, are the transitions among neurons or MUs, the step (l) of **Fig 4.2.1**. As the modelled grid is a discretized space and the system operation is continuous, changes in the operation conditions can provoke transitions among the MUs, which means transitions among different PLR curves. Furthermore, if the operation conditions of the system are not perfectly represented by its BMU, this smoothing provides a continuous behaviour able to adjust the recommendations perfectly to the current conditions. In order to perform this smoothing action to the set point recommendation, a weighted sum of the nearest MUs is made employing the Euclidean distance of each neuron, **Eq. 4.2.2.3**. Thus, the compressors do not change the partial load recommendation abruptly from one neuron to another and the system remains stable in terms of suction pressure.

$$PLR_C = \sum_{i=1}^{K} w_i * PLR_i \qquad \text{Eq. 4.2.2.3}$$

Where $PLR_C$ is the partial load ratio of the $C$ compressor, $K$ is the number of the closer neurons, $PLR_i$ is the partial load ratio recommended by the neuron $i$ and $w_i$ is the weight associated to the neuron $i$. This weight parameter $w$ is calculated using:

$$w_i = \frac{\beta_i}{\sum_{j=1}^{K} \beta_j} \qquad \text{Eq. 4.2.2.4}$$

being $\beta_i$ presented in:

$$\beta_i = \sum_{j=1}^{K} (d_j) - d_i \qquad \textbf{Eq. 4.2.2.5}$$

where $d$ is the Euclidean distance from the sample to the neuron.

### *4.2.2.3 Minimizing the compressors switching events*

Finally, the last part of the method deals with the compressors switching problem exposed before. In this regard, the step (m) of **Fig 4.2.1** is activated when the number of running compressors proposed by the selected PLR vary from the current one. To obtain a robust set point recommendation in this conflictive boundary decision circumstances, a trend classification model of the $Q$ is trained and evaluated to ensure that the switch operation will last at least till a predefined time horizon. If the selected PLR proposes to increase the number of running compressors and the $Q$ trend is positive or if the selected PLR proposes to decrease the number of running compressors and the $Q$ trend is negative, the suggested switch is executed. Differently, if the decisions do not converge in the set point suggestion, the operation is maintained until the next evaluation.

Such switching management is handled with the aforementioned $Q$ trend classification, which is detailed in **Fig 4.2.3**. As the classification is based in historical data retrieved from the database, firstly, in (f.1), the desired target variable, which is the $Q$, is smoothed to highlight the trend and avoid the high frequency noise caused by unpredictable events in the refrigeration system. Once the horizon of the trend classification is set, the smoothed target variable is categorized in three classes, increase, constant or decrease, depending on the slope of the variable, as shown in (f.2). As the problem is interpreted as a classification and to help the later model to improve its accuracy, all the inputs used, which are the variables of the system, are transformed using a feature reduction step, (f.3), such as LDA, to help the posterior model to better infer the trend patterns. Finally, to perform the trend classification at a defined horizon, in (f.4), a MLP neural network is used to detect the trend given the features from the LDA.

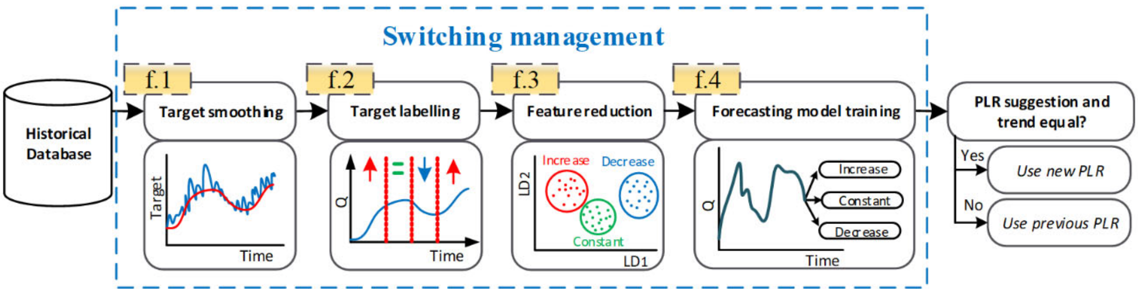



**Fig 4.2.3 - Switching management steps overview.**

Therefore, the switching management method consists in comparing the expected trend of the $Q$ with the proposed PLR switching. Such comparison provides robustness to the decision of switching one compressor with the following logic: if the PLR switching action recommended by the methodology and the trend specified by the MLP are consistent, the switching action can be executed and the PLR suggested by the method is used. Otherwise, if the trend and the current PLR switching action are not consistent, the current PLR is discarded and the previous recommendation is maintained.

## 4.3 Experimental results

The presented methodology is validated in the real refrigeration system described in the Annex I of this thesis. The data used to train the models consist of samples acquired every minute over one year of operation, the same as in the previous chapter, and its partition into train and test sets is done in the same manner, 3 weeks for training and one for testing. The raw variables acquired from the system involved in the methodology are: discharge pressure, suction pressure, compressors partial load ratio, compressors cooling capacity and compressors electrical power.

### 4.3.1 Training and configuration of the methodology

In the near-optimal PLR curves generation, since the methodology is grounded on the previous performance assessment, the first steps (a)-(f) of **Fig 4.2.1** are the same as in the Section 3.3.1, hence, no further details are provided in this chapter.

The first new step of **Fig 4.2.1**, in regard to the Chapter 3, is the (g), where the near-optimal COP is transformed to the near-optimal PLR. To do such task, the PLR values of each sample of the COP curves are selected. Therefore, the best COP samples from each MU are used to extract the PLR configuration of each compressor and obtain the near-optimal PLR curves. **Fig 4.3.1** depicts the aforementioned near-optimal PLR curves of one MU obtained from the proliferation.

In **Fig 4.3.1 a)** appears the raw PLR curves where various irregularities can be appreciated. Such irregularities, should be smoothed in order to avoid abrupt changes in the compressors PLR that may damage the mechanical components and destabilize the system. These irregularities are produced by lack of enough data in certain regions and by the wide discretization areas, which do not contemplate enough resolution to guarantee a continuous and smooth curves. Therefore, to be able to employ such curves in the real system , a smoothing process to the PLR curves is done in order to provide a safe and robust PLR set point recommendation as depicted in **Fig 4.3.1 b)**.

Such smoothing process, which consists in a monotonic filter, is done in the part of the curves where both compressors are running, since in scenarios where only one compressor is operating there is no room for improvement. This filter guarantees that the required PLR to supply the $Q$ always increase at the same time that the required $Q$ increases as well. Thus, incoherent scenarios in terms of abrupt changes in recommendations are mitigated. The monotonic filtering could has also been applied in the opposite direction, however, this increasing direction is chosen in order to ensure that the system is supplying enough $Q$ in all considered scenarios. Subsequently, the stability step is in charge to perform the required slight modifications in $Q$ to preserve the desired refrigerant temperature.

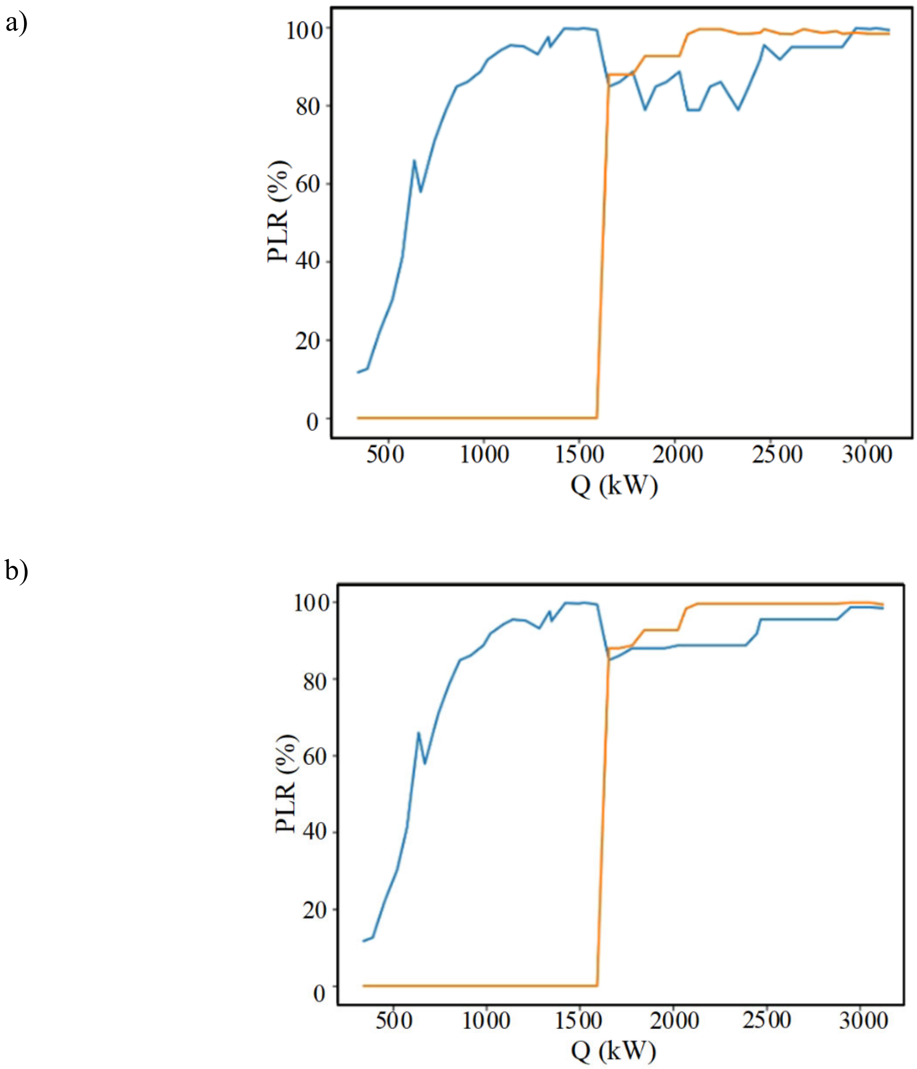



**Fig 4.3.1 –Near-optimal PLR curves example after proliferation of a specific MU. a) Raw curves. b) Processed curves.**

With the near-optimal PLRs generated, the next steps are focused on the parametrization of the set point recommendation part. The aforementioned stability equation, **Eq. 4.2.2.1**, used to modulate the $Q$ to preserve the refrigerant temperature, has the $R$ parameter to be selected. This parameter is used to convert the suction pressure error to a $Q$ value, and should be large enough to surpass to the next segmented $Q$ of the PLR curves and small enough to avoid destabilize the system. There is not a strict rule to select this value, therefore, various empirical tests are performed together with the system experts. With such experiments, the value that accomplishes the aforesaid constraints is 500. Should be mentioned that this value can change depending on the system constrains and characteristics, considering higher values of $R$ correspond to a higher correction ratio.

Another step in the set point recommendation is the smoothing of transitions among different neurons. Such issue is tackled with **Eq. 4.2.2.3**, where the $K$ parameter is the number of neighbours selected in order to perform the smoothing. As in the previous step, there is not a universal rule for this selection. Therefore, since the SOM is configured with a hexagonal lattice to connect its neurons, each MU has 6 neighbours directly connected. Therefore, the selected $K$ value is 6, corresponding to the number of connections.

Finally, the switching management requires the $Q$ trend classification. Consequently, the preprocessed data is used to develop this $Q$ model. Apart from the common preprossessing steps already explained, and in order to reduce the model error, this step perform another transformation of the data. This transformation is done to reduce the noise in the target variable, and for such purpose, an exponential moving average is performed with a 200 samples span. This smoothing technique as well as the span time are selected between various techniques with the validation of the system experts, minimizing the delay response of the smoothing technique and preserving the original signal shape pattern as much as possible.

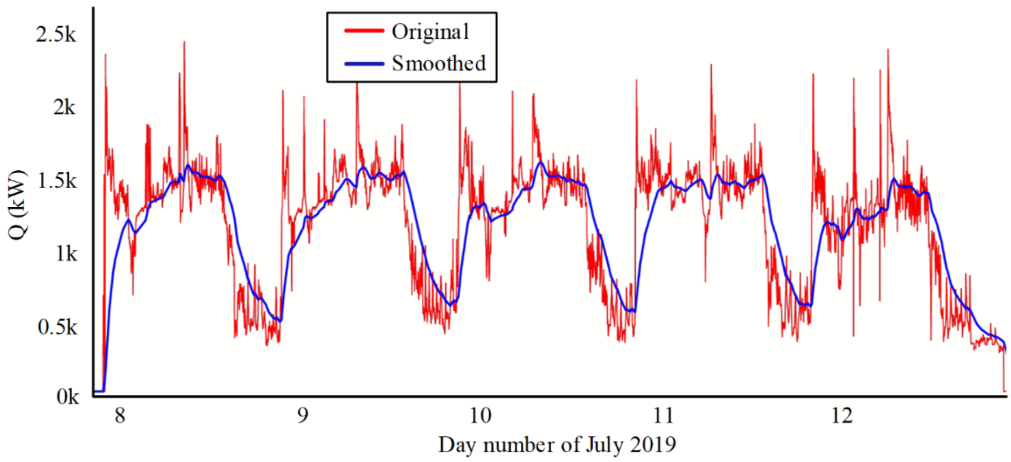



**Fig 4.3.2 – Week detail of the target signal, $Q$, in original shape and smoothed.**

Later, with a prediction horizon of 20 minutes, selected by the system experts, the target is divided in three different categories: positive, negative and neutral. According to the experts, this horizon is the minimum time required between two compressor switches. The three categories are labelled regarding the $Q$ trends within the defined horizon: positive, if the target has increased more than 1.5% , negative, if the target has decreased more than 1.5% and neutral if the target has been between $\pm 1.5\%$.

As initial inputs to do the trend classification, the signals from the DDBB mentioned at the beginning of this section are used. However, some of them are dismissed due its high correlation values as the electrical consumptions versus the PLRs. A part from the aforesaid variables, to provide more information about past values to the model, some lags of the target signal are also used. All the variables employed to train the model are displayed in **Table 4.3.1**.

**Table 4.3.1 - Variables employed for the cooling capacity trend model. Timesteps have a sampling rate of one minute.**

| Variable | Unit | Description |
|---|---|---|
| $Q_{,t}$ | kW | Cooling capacity at the current timestep *t*. |
| $Q_{t-1}$ | kW | Cooling capacity at time *t-1*. |
| $Q_{t-2}$ | kW | Cooling capacity at time *t-2*. |
| $Q_{t-3}$ | kW | Cooling capacity at time *t-3*. |
| $dp_t$ | Bar | Discharge pressure at timestep *t*. |
| $PLR_{i,t}$ | % | Partial load ratio of compressor *i* at the current timestep *t*. |
| $sp_t$ | Bar | Suction pressure at timestep *t*. |

At this step, all the variables to build the model are prepared, however, since the trend model is approached as a classification problem and the target is imbalanced, all the classes are balanced to improve the accuracy and reduce the bias produced by the nature of the dataset [152].

The dimensionality of the already balanced and scaled inputs, is reduced to two components by means of the LDA projection in order to be finally used as the model inputs. The classification accuracy with such dimensionality reduction is often significantly better than with the original dataset [153]. Therefore, the LDA feature reduction technique is used as it maximizes the distances between the different classes, increasing the posterior algorithm accuracy. As **Fig 4.3.3** shows, in this scenario the algorithm cannot separate in a clear way the different classes: increase, neutral and decrease trends. This happens as the system variation is continuous and the transitions among the different classes are not discrete. Nevertheless, with this dimensionality reduction technique, the operation trend can be identified as it is highly correlated with the x axis of the LDA projection, improving the subsequent classification.

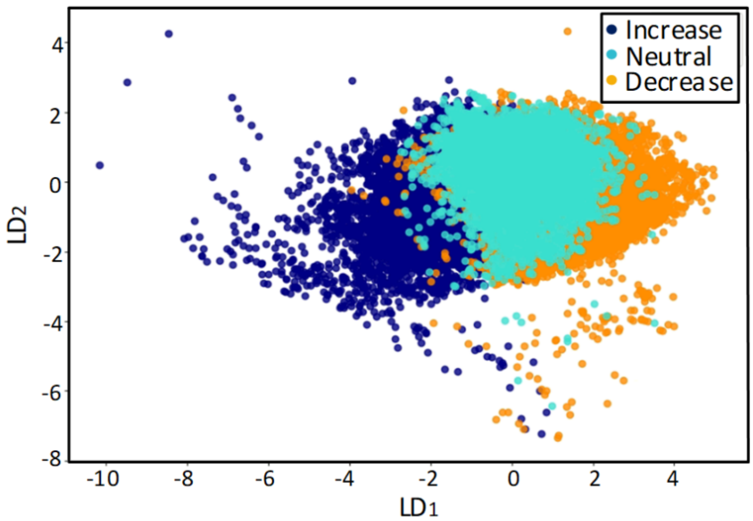



**Fig 4.3.3 - 2D LDA representation with the different target labels coloured.**

Afterwards, the obtained features from the LDA are input to the model. The chosen model is a MLP configured with two hidden layers of 16 neurons each one with a ReLU and as many outputs as classification classes with a softmax activation function. The optimizer used is the SGD with a learning rate of 0.001 and the loss function is the categorical cross-entropy. All the parameters selected for the MLP configuration are chosen using a grid search with multiple options and cross-validation with accuracy as performance metric, both techniques employed to avoid overfitting while selecting the best parametrization. The accuracy of the model in the test set is about 70% and the confusion matrix is shown in **Table 4.3.2**.

**Table 4.3.2 - Confusion matrix of the trend classification test data.**

| | Decrease (Predicted) | Increase (Predicted) | Neutral (Predicted) |
|---|---|---|---|
| **Decrease (True)** | 64.77 | 6.70 | 28.53 |
| **Increase (True)** | 2.47 | 72.38 | 25.15 |
| **Neutral (True)** | 14.26 | 19.77 | 65.97 |

The obtained accuracy, despite not being really high, is robust in terms that the vast majority of the errors are not between the decrease and increase states, which would lead to a machinery inefficiency. Furthermore, such performance is attributed to the lack of information about the cooling load. The different processes in the industry related with the refrigeration system can vary its cooling load substantially depending on the operators' behaviour and process requirements. However, information in regard the cooling load is not available in the process.

### 4.3.2 Evaluation of the method in the refrigeration system

To highlight the advantages of the methodology in terms of savings, two particular cases are presented using the test dataset: the first one in which the new optimal partial load ratios are suggested in the scenario where high cooling capacities are demanded and two compressors are needed undoubtedly, and the second one in which the PLRs are recommended during cooling capacities that let to switch one of the compressors.

Finally, to evaluate the overall contribution of the proposed methodology, the method is applied in real-time in the refrigeration system in scenarios where two compressors were needed.

#### *4.3.2.1 Results – Scenario 1: two compressors*

During this first scenario of the refrigeration system operation, the original control scheme maintains the PLR of both compressors (C1 and C2) under similar and constant values, instead of customize it to maximize the COP, such behaviour can be seen in **Fig 4.3.4 a)**. In comparison, in the same scenario, the proposed methodology analyse the operation condition of the refrigeration system and recommend a different PLR for both compressors, obtaining the desired cooling capacity but minimizing the electrical consumption, such difference can be seen in **Fig 4.3.4 b)**.

a)

b)

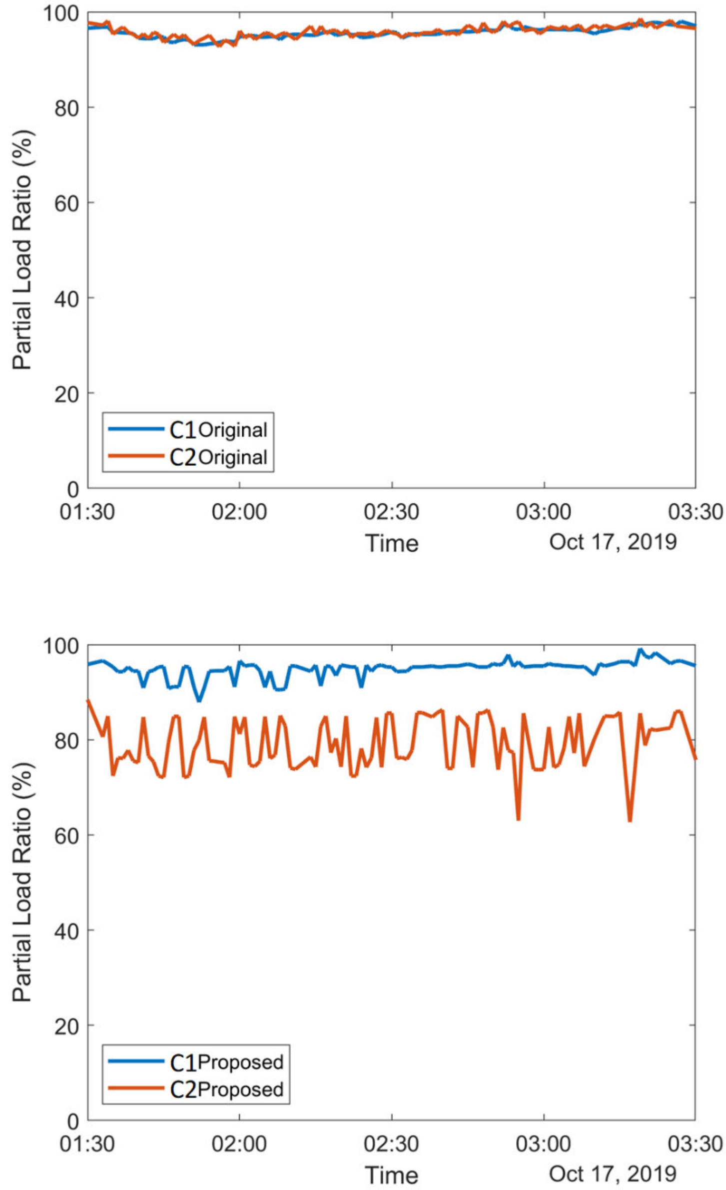
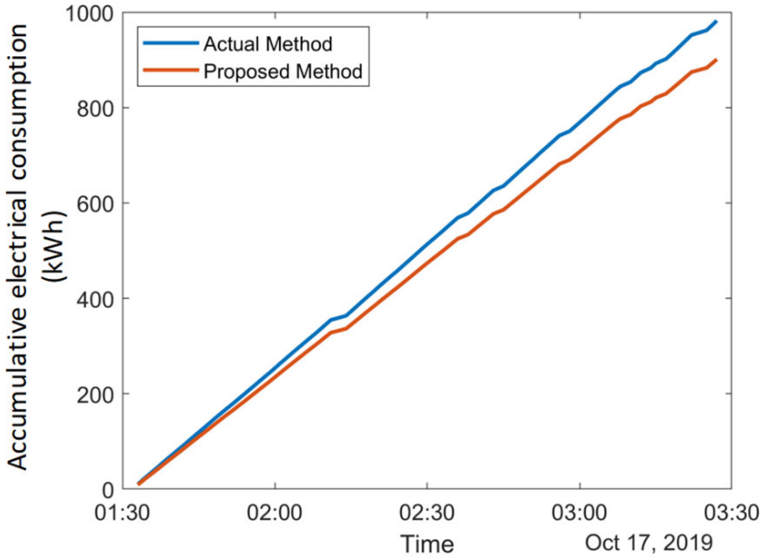



**Fig 4.3.4 - Comparison detail of the original control versus the proposed methodology in the 2 compressors scenario. a) Current PLRs strategy. b) Proposed methodology PLRs.**

Nevertheless, the aforementioned PLR recommendations employing the test set cannot be directly obtainable in a real industrial system as these recommended PLR set points cannot be reached immediately. Each compressor has its slide valve to regulate its PLR, such mechanism has its dynamics and it is controlled by a PID. Such control has its settling time to achieve the desired set point and its overshot, making unfeasible to follow exactly the theoretical recommendations. However, the results show that there is still room for improvement modulating the compressors PLR.

Despite the aforementioned control particularity, the accumulative electrical energy consumed by both approaches are compared in a period of time in order to illustrate the efficiency improvement capabilities. It can be seen in **Fig 4.3.5 a)** that the proposed method achieves a lower consumption (80kWh) over the two-hour comparison. Such difference is highlighted in **Fig 4.3.5 b)** in terms of savings, which corresponds to a 7% per hour of the average electrical consumption in this scenario.

a)




b)

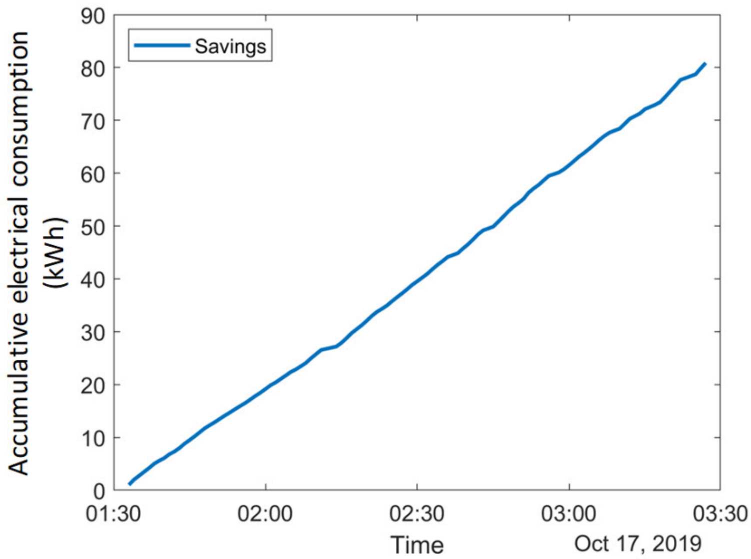



**Fig 4.3.5 – Detail of the electrical energy savings analysis. a) Accumulative electrical consumption comparison between current strategy vs proposed methodology. b) Accumulated electrical savings using the current strategy as reference.**

*4.3.2.2 Results – Scenario 2: compressors switching.*

When transitions of operating compressors occur due to the cooling capacity demand, the optimal switching time management depends on the trend of the demand, and the COP can be maximized if the PLRs control of the compressors consider such trend. A specific scenario that can reduce the electrical energy consumption is when the cooling demand will decrease and, therefore, a transition from two compressors to one occurs. The optimal time management of such switching of compressors is estimated by the proposed methodology and thus, a reduction of electrical consumption is achieved. Such example can be seen in **Fig 4.3.6 a)**, where the actual control strategy proposes to turn off the compressor C1 at 8:50am, but the proposed methodology identifies the demand decrease trend and turns off the same compressor 10 minutes earlier. The difference in both strategies can be seen in **Fig 4.3.6 b)**, in which a significant difference in electrical energy consumption can be appreciated at the switching period of time.

To highlight the importance of the trend model and the difference of both methods, the accumulated savings can be seen in **Fig 4.3.6 c)**. In the first minutes, when two compressors are operating, the aforementioned scenario 1 that achieves a mean savings of 7% per hour can be appreciated. Nevertheless, an increase in the slope of the accumulated savings curve should be noticed when the transition of the compressors occurs, leading to a 15% of electrical consumption savings in such situation. The combination of both scenarios led to an accumulative savings of 12% during the tested period.

Contrarily to the first scenario, where peculiarities of the control involved in the PLR recommendation limit its fully applicability in the real industrial systems, this one can be easily implemented, which highlights the significance of the results. When the set point recommendation methodology suggests to switch a compressor, the real system can follow it almost instantly. Such improving in the switching situations suppose an additional savings in this PLR recommendation methodology. These switching scenarios are not usual during a common day of operation, however, during a whole month it is estimated that can suppose around an additional 1000kWh of savings.

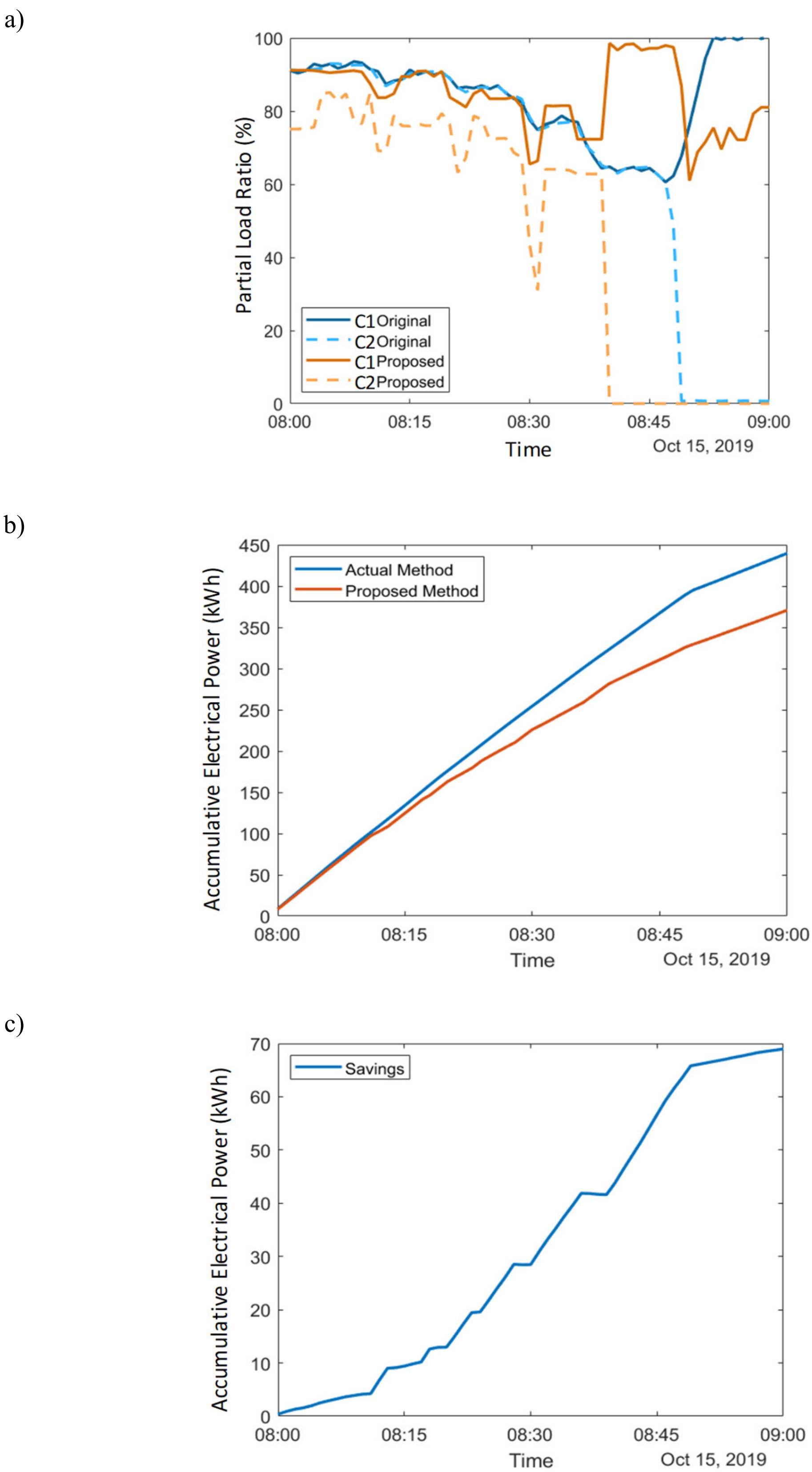



**Fig 4.3.6 - Comparison detail of the original control versus the proposed methodology in the switching compressors scenario. a) PLR strategy. b) Accumulative electrical energy. c) Savings of the proposed method using the original control as reference.**

#### *4.3.2.3 Results – Online validation*

To analyse the performance with the real system, the training and test sets are dismissed, and the compressors PLR control of the refrigeration system is changed to the proposed methodology. To do such task, a battery of tests distributed in hourly periods where two compressors are needed and with different $Q$ values, is performed. To obtain the savings, the electrical energy consumed hourly by the methodology is compared with a reference. The reference is the most similar hour of operation taking into account the external factors, that are the suction pressure, the discharge pressure and cooling capacity of the available historical dataset. Therefore, a realistic comparison can be made as the operation conditions of the compressors are very similar as shown in **Table 4.3.3**.

**Table 4.3.3 - Samples with the proposed methodology applied in the refrigeration system versus similar samples from the database used as a reference. Tests of 1 hour of operation.**

| | | ***Q* (kWh)** | **Suction P (bar)** | **Discharge P (bar)** | **C1 PLR (%)** | **C2 PLR (%)** |
|---|---|---|---|---|---|---|
| **TEST 1** | Proposed | 1375 | 1.61 | 8.32 | 73 | 81 |
| | Reference | 1360 | 1.58 | 8.38 | 78 | 78 |
| **TEST 2** | Proposed | 1439 | 1.65 | 8.26 | 72 | 88 |
| | Reference | 1435 | 1.59 | 8.13 | 83 | 83 |
| **TEST 3** | Proposed | 1535 | 1.61 | 9.93 | 80 | 92 |
| | Reference | 1541 | 1.60 | 9.94 | 90 | 90 |
| **TEST 4** | Proposed | 1686 | 1.61 | 10.05 | 84 | 96 |
| | Reference | 1699 | 1.59 | 10.11 | 94 | 94 |

With the similar samples used as a reference, a comparison regarding the electrical energy expenditure during these tested hours is performed. Thus, the electrical consumption reduction can be appreciated as **Fig 4.3.7** shows.

In the figure, it is appreciable the reduction in electrical energy employing the proposed PLR recommendation. A mean of 4.4% per hour is saved which represents around 26kWh per hour. It should be noticed that the improvement capabilities managing the PLRs increase with the cooling capacity needed. With lower $Q$ the management has less effect on the performance, this fact agrees with the typical COP curve of this compressors, already seen in Chapter 3. On the other hand, even though it was not possible to test due to the demand requirements, the differences between the proposed methodology and the current operation should be minimized approaching the maximum capacity. This fact is assumable as when the system reach its limit there are no possible alternative PLRs to supply such $Q$.

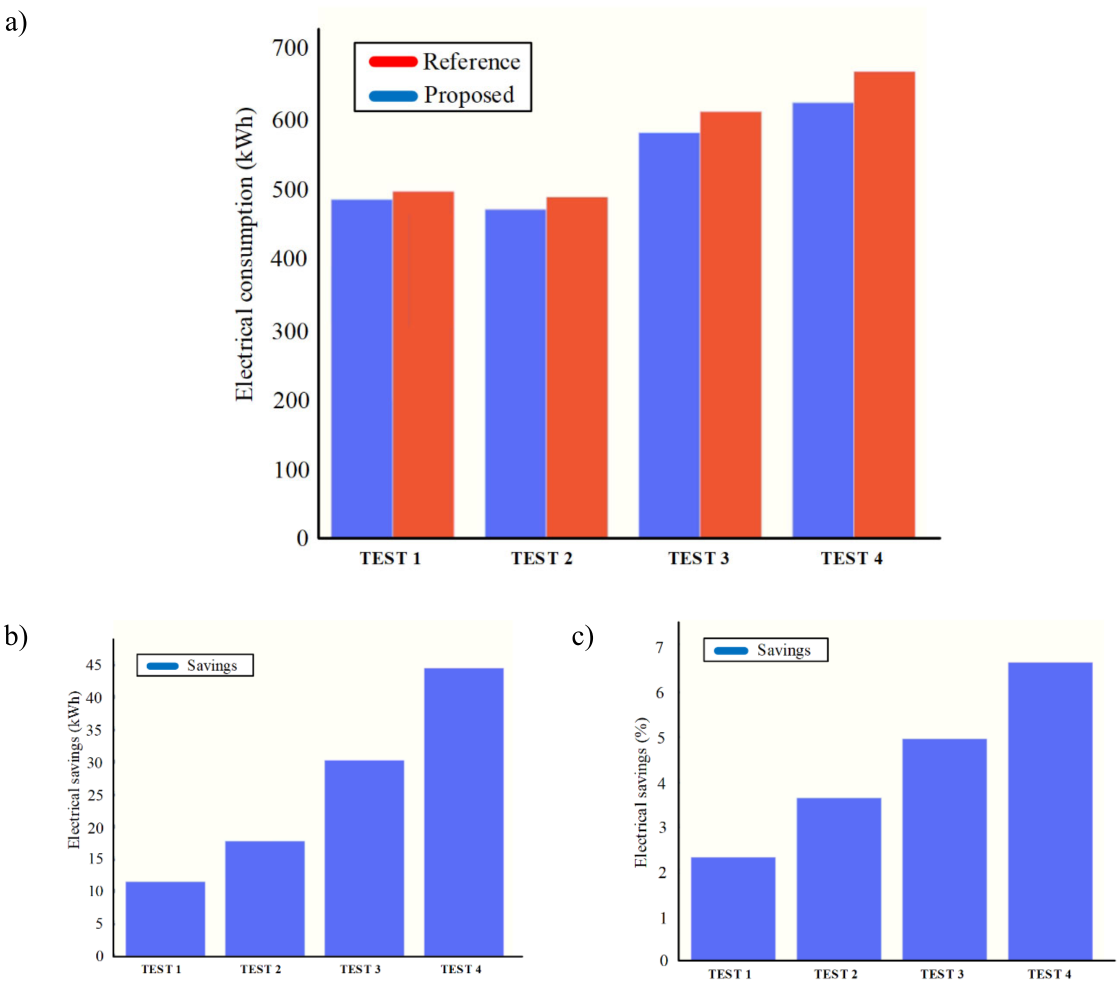



**Fig 4.3.7 - Electrical consumption analysis of the proposed methodology. a) Reference vs proposed method. b) Absolute savings. c) Percentage savings.**

Furthermore, as shown in **Fig 4.3.8**, the refrigerant temperature, which is measured with the suction pressure, has low error in regard to its set point and is able to maintain the system stable thanks to the strategy applied to modify the $Q$ values. To be able to compare the obtained errors with a reference error of the classical PLR control, the mean suction pressure error value of the dataset is calculated. Thus, it is appreciable that the proposed PLR set point recommendation is able to maintain the refrigerant temperature as well or even better than the classical approach while maximizing the compressors efficiency.

The presented results indicate the capabilities of the recommendation methodology optimizing the compressors PLR. The proposed solution is robust and fast enough to be applied in real-time in an industrial refrigeration system with promising results. However, as mentioned previously, the real savings of the methodology are reduced regarding the theoretical ones due to the impossibility of the control to follow exactly the desired recommendation set points. Moreover, the switching management proportionate additional savings in such situations while maintaining the machinery safe.

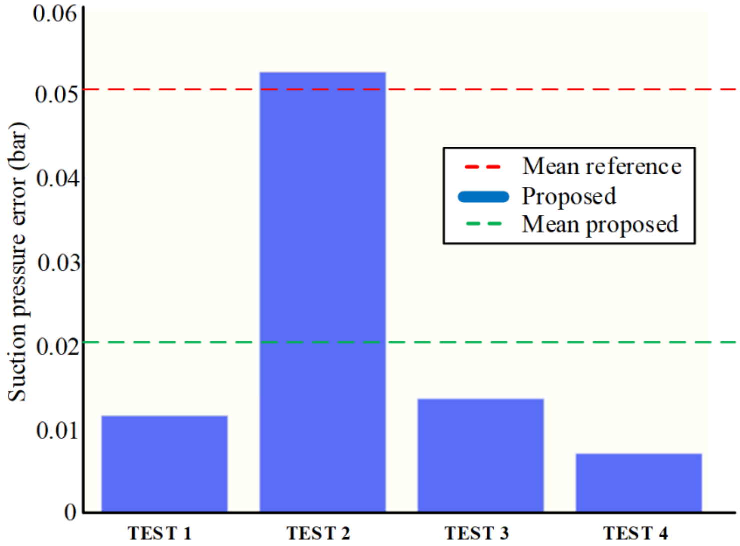



**Fig 4.3.8 - Suction pressure error of each test. The mean error of the proposed strategy is lower than the current operation.**

## 4.4 Conclusions and discussion

The proposed methodology addresses the PLR recommendation considering the operation conditions and the demand trends while maintaining the system within the desired stable conditions. With such considerations, it is able to recommend near-optimal set points in any known scenario in order to maximize the compressors efficiency.

For the aforementioned purpose, various concerns in regard to reliability and robustness are taken into account in order to apply the methodology in an industrial refrigeration system. First of all, the set points provided by the methodology are robust to unknown scenarios to provide safety recommendations in industrial conditions. Such characteristic is ensured by means of the preprocessing and uncertainty steps that grant the capability to reject recommendations where the conditions are not similar to the historical operation. If this property is not considered, the methodology could recommend non-trustworthy set points that can damage the machinery and the quality of the product.

The aforementioned set points ensure reliability as they take into account the different variables that affect the system operation. This feature is accomplished discretizing the operation space and generating the near-optimal PLRs in each discretized area. Additionally, and ensuring the reliability as well, the proposed PLRs overcome the historical operations taking advantage of the proliferation technique. Such property enlarges the database operation casuistry giving the possibility to obtain artificial PLR scenarios. Thus, the system achieves better performances with the estimated artificial scenarios, providing the advantage that these artificial scenarios do not need to be previously tested in the system.

Apart from the robustness in unknown scenarios and the aforesaid reliability, other issues appear in industrial conditions in order to apply a data-driven methodology in a robust manner. In this case, such issues refer to the refrigerant temperature constraint, the smooth modulation of the compressors PLR and the switching management.

The refrigerant temperature, evaluated employing the suction pressure, is guaranteed applying a cooling capacity shifting strategy that considers the suction pressure error. Such strategy has the capability to modulate the $Q$ value, and the PLR indirectly, in order to stabilize the refrigerant temperature.

In regard to the compressors smooth PLR modulation, the methodology ensures a smooth transition between neurons to avoid abrupt PLR modifications in the compressors. For this purpose, the neighbour neurons of the BMU are selected to obtain a weighted PLR recommendation.

Ultimately, a trend classification is used to solve the switching management issue. Such trend identification is able to select the right moment to switch on or off a compressor. That fact avoids unnecessary switches that may reduce the RUL of the machinery and increase the system efficiency providing additional savings.

To validate the proposed methodology, two tests are made: the evaluation of the set point recommendation in historical scenarios and the recommendation in the system in real-time. For the first validation, where the historical results are compared with the recommendations that the methodology would have made, the test dataset is used highlighting two scenarios: when two compressors are operating in parallel and when there is a switching situation. This theoretical results confirm the effectiveness of the methodology obtaining meaningful savings in both scenarios, with higher percentages but shorter in time in the switching one. These less frequent switching situations offer additional savings to the whole methodology apart from robustness in the switching decision.

On the other hand, the methodology is validated in real-time in the industrial refrigeration system, obtaining satisfactory results. It is concluded that with higher cooling loads, the methodology obtain higher efficiencies compared with the classical control strategy. Nevertheless, the results in the real system present a significant reduction in savings compared to the test set. This fact is attributed to the intrinsic PLR control dynamics which presents substantial delays and deviations in order to reach the suggested PLR recommendation. Such concern, is tackled in the next chapter proposing a load balancing strategy that can reduce the abrupt changes in the load behaviour. Thus, the current control will be able to follow the recommended PLR in a more reliable way as the changes in the PLR set point will be even smoother.

# 5.

## Load management

This chapter tackles the refrigeration system efficiency optimization from the load side. A disaggregation methodology is presented to quantify the consumption of each machine in each space to refrigerate. Subsequently, a load balancing strategy is formulated with the aim to obtain consumption savings managing the loads.

CONTENTS:

# 5 Load management

In this chapter, a load management methodology is proposed. Such methodology is composed by a novel non-intrusive energy disaggregation and a real-time load balancing strategy that takes advantage of the previous load disaggregation knowledge. The methodology aims to be aware of the consumed energy and reduce the non-efficient load peaks. All the proposed techniques are validated using the industrial refrigeration system.

## 5.1 Introduction

In this section, the background and motivation of the topic are outlined and the innovative contributions of the proposed methodology are described.

### 5.1.1 Background and motivation

In energy management systems, the actions to reduce the energy consumption or increase its efficiency are not limited to the generation side and its proper configuration. A great efficiency impact can be also achieved managing the load side accurately. Approaches such as the reduction of load peaks, which minimizes the starting of more machines, or the modulation of the load to operate in efficient partial load ratios, are clear examples of such impact. Thus, in industrial systems or more specifically in refrigeration systems where all the loads belong to the same facility, it is of vitally importance to develop load management strategies to mitigate this non-desirable consumption patterns and increase the system efficiency.

One of the prerequisites to exploit the load side management enhancement possibilities, is the identification and monitoring of each connected load of the system. Without the knowledge about the consumption contribution of each appliance or device it is not feasible to propose adequate improvement strategies. Although the necessity of this information, in most scenarios is non-viable to measure the consumption of each appliance due to the high cost that the instrumentation entails. To overcome such limitation, several NILM methodologies, which do not need instrumentation, appear in literature. However, as stated before in the state of the art chapter, most of the data-driven NILM techniques require previous labelled data to be able to create the different appliances models. Hence, at least some benchmark devices should be monitored in order to perform the aforementioned techniques, what is still an important shortcoming.

In addition, all the current techniques are based on identifying the electrical consumption, which in the particular case of the refrigeration systems, is not useful as the load should be computed using the cooling load. The mentioned cooling load is important as the electricity expenditure in refrigeration systems is directly related with the amount of heat to remove from the space. Hence, the load is not only affected by the number of switched appliances, in this case evaporators, but also with the amount of mass to cool and its temperature. Furthermore, all the evaporators can be from different capacities, have similar consumption signatures and its consumption is continuously changing due to the constant introduction and removal of cooling loads. Observing all the summarized current literature drawbacks, the explained challenging difficulties of cooling loads, and the few studies made by the research community regarding this topic applied in refrigeration systems, suggest that there still way to explore new methodologies taking into account the aforesaid particularities.

On the other hand, assuming that the load of the different appliances is known, various strategies to avoid consumption peaks and huge simultaneities are also presented in literature as mentioned in the state of the art. These strategies can provide successful results in scheduled environments but lack of adaptability in industrial scenarios where the loads are constantly changing, such as in refrigeration. As mentioned, in most of spaces to refrigerate, the operators put and remove different loads depending on their jobs necessities and contribute to the fluctuating load. Furthermore, the majority of the current studies are applied in residential building where a slight management error can only affect the users comfort. However, in most of the industrial processes needed to be refrigerated, it is crucial to maintain the desired product at specific conditions to ensure its quality, not giving room for unexpected temperature modelling errors.

As has been described, the particularities of the industrial refrigeration case, make unfeasible the application of current solutions requesting further studies to adapt the load management methodologies to a real-time industrial scenario. A proper management of the load peaks can benefit the operation of refrigeration systems avoiding unnecessary switch of compressors, which is favourable to prevent malfunctions and maintenances, and diminishing in a substantial way the electrical energy consumed.

In conclusion, having analysed and discussed the topic background in the refrigeration framework, it is perceptible that more efforts should be employed to overcome this challenging issues in the refrigeration systems in order to create useful and applicable methodologies for an industrial environment. This chapter proposes a specific approach to overcome some of the current limitations.

### 5.1.2 Innovative contribution

Pretending to overcome some of the mentioned drawbacks, a data-driven methodology able to operate in real-time conditions is proposed. First of all, regarding the energy disaggregation prerequisite, a novel NILM methodology for identifying cooling loads, instead of the electrical loads, is presented. This NILM methodology is a semisupervised technique that takes advantage of the data acquired from the refrigeration systems, a notorious benefit of the majority of the industrial processes due to its centralized control and data acquisition systems. With this monitored data, and with a novel neural network structure, the proposed method is able to estimate the individual consumption of each cooling load without the need of labelled data.

*The **non-intrusive load monitoring methodology for cooling loads** takes advantage of the monitored variables in refrigeration systems and **do not need** historical **labelled data** to model each load.*

Furthermore, and using the disaggregated data, a load balancing algorithm is suggested being totally independent of forecasting assumptions that could lead to undesired temperature errors. Reliable individual load forecasts are difficult to obtain due to the stochastic behaviour of the processes and its operators. Therefore, such forecasts are dismissed to avoid undesired quality losses in the product. In addition, the load balancing to smooth the consumption peaks is performed in real-time, making its applicability suitable for delicate and highly variable refrigeration processes.

*The **data-driven load management** methodology **takes advantage of the disaggregated loads** to recommend which loads should be refrigerated while maintaining its temperature set point.*

## 5.2 Load management methodology

To approach the load management problem, a methodology that embodies the two aforementioned essential necessities is proposed: the disaggregation and balancing of the load. The two main steps are depicted in **Fig 5.2.1**, where the first one is the part which solves the individual energy monitoring issue by means of a disaggregation strategy. And the second one takes advantage of the disaggregated loads to balance the consumption in order to improve the system in terms of electrical consumption.

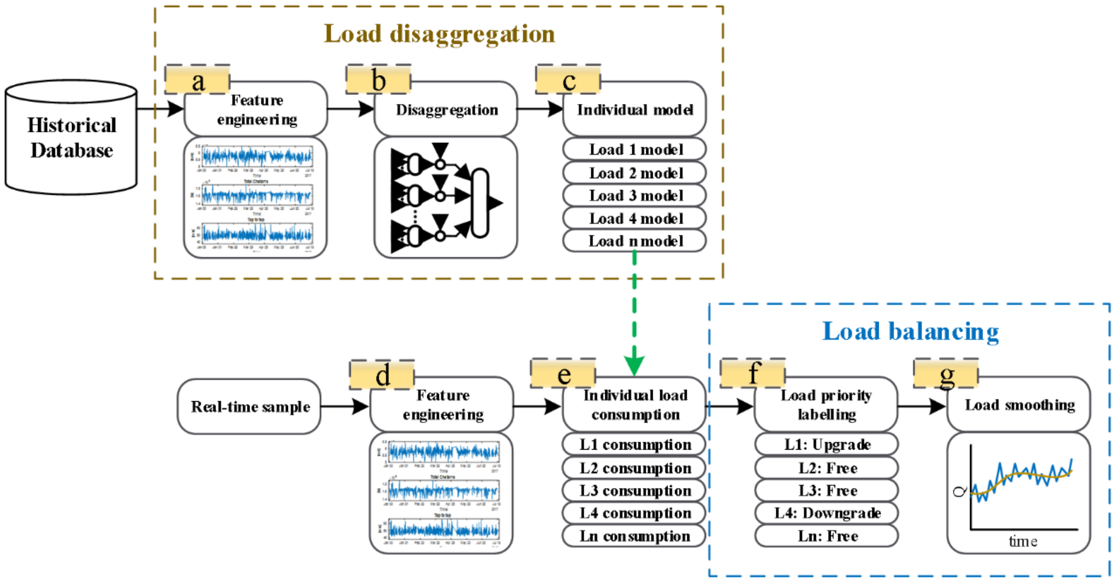



**Fig 5.2.1 - Load management methodology overview.**

Initially, the model of each individual cooling load is obtained using only the historical operation data and the aggregated consumption as target. Due to the impossibility to acquire labelled data from the system to train the models, and taking advantage of the benefits of having historical operation data, a semisupervised technique is proposed to solve this NILM problem.

First of all, in (a), a feature engineering step is employed to develop new appliance characteristics based on its operation information, such as the elapsed time since the machine was turned on/off or the number of machines operating. These new features are used as inputs of the subsequent step to improve the system description and disaggregation capabilities. Afterwards, the algorithm designed for the disaggregation task is trained using the aggregated consumption data as target and the previously computed features, together with the system signals, as inputs (b). Finally, and to finish this first disaggregation module, the model of each load is obtained separately thanks to the algorithm structure (c). As the disaggregation methodologies applied to cooling loads are not widely studied in the literature, the disaggregation methodology presented in this thesis represents a significant contribution to the current state of the art.

With the disaggregation task completed, the second step is in charge to smooth the demand curve in order to improve the efficiency in the generation side of the system. Due to the particularities of the refrigeration systems explained above, the methodology adopts a real-time load balancing solution to maintain the load temperature set point under highly variable situations and avoid forecasting assumptions.

The new data acquired from the system PLCs is used to perform the same feature engineering (d) as in the disaggregation step. Thus, the same features can be used to identify the individual consumption of each load. To accomplish such task, and besides the mentioned features, the models created in the previous step are also utilized (e).

Following, the demand necessities of each space to refrigerate, hereafter named (S), which can be e.g. a cooling tunnel, a cooling chamber, etc., are evaluated in regard to the temperature set point together with the current temperature and its variation. To do such task, each S is labelled in step (f) to increase or diminish its power consumption and also, to be able to recognize the spaces to refrigerate that can be used to modulate and balance the whole consumption. The aforesaid labelling is performed using the tags: increase, when more power its necessary to refrigerate the space, decrease when the space is colder than its necessary, or free to designate the spaces which are within its correct temperature range. Thus, the product temperature conditions are guaranteed and never altered by the balancing strategy as the modifications are done only with the spaces with the free label. The selection of the rules for such labelling parameters is critical for product quality, hence, they should be chosen by process experts taking into account the kind of load that each S work with.

Finally, the last module (g) manage the free loads to combine them in order to smooth the demand response, which is the final objective of this methodology. In this regard, this module is in charge of modifying the evaporators management of the loads that are within its desired temperature bounds, to smooth as much as possible the aggregated consumption curve, $Q$, and be able to operate the compressors in a more efficient PLR. This aspect also benefits the methodology presented in the Chapter 4, since with a smoothed $Q$, the control should be able to follow the recommended PLR set points more precisely.

### 5.2.1 Load disaggregation

The disaggregation or NILM methodologies commonly applied to the electrical power, present two main difficulties when applied to refrigeration systems. First, since all the refrigeration spaces to refrigerate are provided, mostly, with the same machinery and have analogous behaviour, the cooling load signatures are very similar. This particularity increases the difficulty to identify each individual appliance consumption. Second, since the cooling capacity is highly dependent on the compartment cooling load and its temperature, the consumption is continuously varying which increase the difficulty to obtain a steady operation consumption.

To tackle such issues, the proposed semisupervised approach takes advantage of the sensors installed in common refrigeration systems as additional information. Hence, the data acquired from the instrumentation is used to create a data-driven methodology to disaggregate the whole cooling load of the system as detailed below.

This cooling load disaggregation methodology takes various steps in order to determine the contribution of each load as depicted in **Fig 5.2.1**. In the subsections below, a detail of each step is provided concluding with a proper validation using a mathematical simulation.

### *5.2.1.1 Feature engineering*

First, with all the data available from the database, the signals that can influence the cooling load are selected and new ones are created in order to describe more accurately the system behaviour. This task, called feature engineering, is done to improve the learning performance of the subsequent modelling methodology [154]. The variables used and the additional generated features, shown in **Table 5.2.1**, are related with the machinery in charge to refrigerate the different spaces and the spaces themselves. Thus, this feature engineering step increases the robustness of the model regarding the transient states during machinery commutations and its associated dynamics, which lead to a more reliable estimation of the disaggregated signals.

**Table 5.2.1 - Features employed for the disaggregation methodology. The artificially created ones from the original data are displayed in grey.**

| Feature | Unit | Description |
|---|---|---|
| $T_{s,t}$ | ºC | Temperature of the space *s* at the current timestep *t*. |
| $T_{s,t-1}$ | ºC | Temperature of the space *s* at time *t-1*. |
| $T_{s,t-2}$ | ºC | Temperature of the space *s* at time *t-2*. |
| $T_{s,t-3}$ | ºC | Temperature of the space *s* at time *t-3*. |
| $\tau^{g}_{s,t}$ | Timesteps | Number of timesteps elapsed since the evaporator *g* of the space *s* was switched ON at the current timestep *t*. |
| $\varphi^{g}_{s,t}$ | Timesteps | Number of timesteps elapsed since the evaporator *g* of the space *s* was switched OFF at the current timestep *t*. |
| $G_{s,t}$ | Units | Number of evaporators switched ON at the space *s* at the current timestep *t*. |
| $sp_t$ | Bar | Suction pressure |

All the selected and calculated features are subsequently employed as inputs in the proposed neural network structure formed by various MLP networks and custom layers. The aforementioned MLP network is a type of ANN which is grouped into one of the most common ANN categories, the feed-forward networks[155], described as a powerful tool to model non-linear functions [156]. Although this type of NN is extensively explained in literature, a brief introduction to its basic operation is presented in order to clarify the subsequent description of the proposed neural network structure.

### *5.2.1.2 From the neural networks basics to the MLP: a brief introduction*

To provide further detail about the basic principles of the MLP, a brief description about the basics of the ANNs is provided. The foundations and principles of operation of ANNs were introduced by McCulloch and Pitts [157], which were inspired by the central nervous system with their neurons, dendrites, axons and synapses. The main processing unit of an ANN is the neuron, illustrated in **Fig 5.2.2**, where the inputs are multiplied by the connection weights coming from the previous layer, the different results of the past operation are summed, and finally passed through a transfer function to produce the output [157].

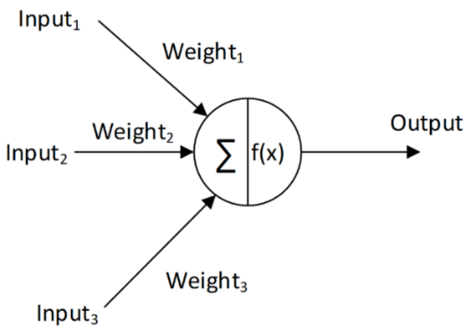



**Fig 5.2.2 - Artificial neuron model.**

This characteristic behaviour of the neuron is described in **Eq. 5.2.1.1**, where the $x_z$ is the *z-th* input and the $w_z$ is the *z-th* weight. Different transfer functions, $f(x)$, exist in literature and are used to determine the output of a processing neuron. Typical transfer functions are the sigmoid, the hyperbolic tangent, the step, the ramping, the arc tan or the linear [158].

$$f\left(\sum w_z x_z\right) \qquad \textbf{Eq. 5.2.1.1}$$

Having described the main processor unit, the neuron and its operation, the next step is to describe the MLP network, which is constructed by several neurons. The MLP is a structure composed by various neurons distributed in layers utilized to generate complex relationships among its inputs and outputs. A common MLP structure is shown in **Fig 5.2.3**, where the input layer, the hidden layer and the output layer are depicted along with its typical connections. All the neurons of the MLP have the same operation as described in **Eq. 5.2.1.1** except the neurons in the input layer that only represent an input feature.

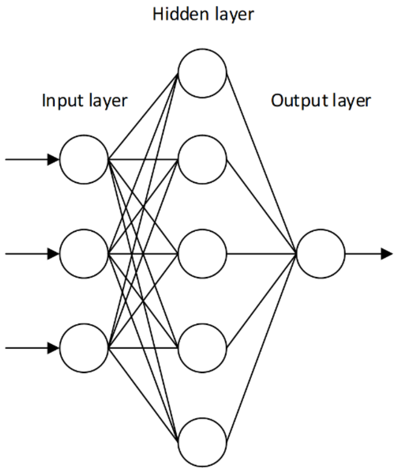



**Fig 5.2.3 – Multi-layer perceptron network example with one hidden layer.**

The capacity to model the target behaviour, which is the desired signal to mimic, creating the aforementioned relationships between the inputs and the target, resides in the weight adjustment of each connection. This weight update is done during the training phase where the algorithm is continually varying the weight values in order to minimize the error between the target and the predicted output. The common error function used is the MSE shown in **Eq. 5.2.1.2** and **Eq. 5.2.1.2** [159]:

$$MSE \equiv E \equiv \frac{1}{K}\sum_{k=1}^{K} MSE(k) \qquad \textbf{Eq. 5.2.1.2}$$

$$MSE(k) \equiv E(k) \equiv \frac{1}{P}\sum_{p=1}^{P}\left(y_p(k) - \hat{y}_p(k)\right)^2 \qquad \textbf{Eq. 5.2.1.3}$$

where $K$ is the number of samples in training, $P$ the number of output neurons, which is set to one in regression problems and $y_p(k)$ and $\hat{y}_p(k)$ are the *p-th* target and predicted output for the sample $k$ respectively.

In order to minimize the error while training the network, the BP technique along with different optimization algorithms such as gradient descent, Adam or RMSprop are commonly used [160]. First of all, the BP algorithm initialize the weights with random values and afterwards, through various iterations and with the help of the optimizer, the weights are updated to minimize the error. Two main approaches to iterate these weights exist: the batch update and the individual update [159]. The batch update consists in evaluate various samples before update the weights, **Eq. 5.2.1.4**, whereas the individual modify the weights after each sample input **Eq. 5.2.1.5**, being more computationally expensive during the training step.

$$^{*}\boldsymbol{w} = \boldsymbol{w} - \eta\left(\frac{\partial \boldsymbol{E}}{\partial \boldsymbol{w}}\right)$$ **Eq. 5.2.1.4**

$$^{*}\boldsymbol{w} = \boldsymbol{w} - \eta\left(\frac{\partial E(k)}{\partial \boldsymbol{w}}\right)$$ **Eq. 5.2.1.5**

The nomenclature of the **Eq. 5.2.1.4** and **Eq. 5.2.1.5** is as follows; $\eta$ refers to the learning rate, $\partial$ to the derivative, **E** is the vector of errors and $\boldsymbol{w}$ is the vector of weights, using an * to identify the new weight. This learning rate, which is a configurable parameter of the most common optimization algorithms, is used to avoid local minimums and adjust the learning computation time. More details can be found in literature about the influence of the BP parametrization, optimizers and its fundamentals [156].

In the subsequent section, the particularities of the weight updates and the custom layers functionality of the proposed disaggregation methodology are explained. These characteristics make feasible the estimation of the individual loads employing the whole consumption signal as a target.

### *5.2.1.3 Proposed network structure*

With the MLP already explained and taking advantage of its ability to model non-linear behaviours, the proposed network structure is shown in **Fig 5.2.4**. As has been aforementioned, the structure uses the various inputs selected and created in the feature engineering part to model the aggregated consumption signal while estimates the individual contribution of each load. Even though the structure is trained with the aggregated consumption, the final purpose of the structure is to estimate the individual load of each S.

The structure is made up by three main layers: the *SNN*, which by adjusting the weights of the neurons is able to model each S, the *M* layer, which activates or deactivates the output and the weight update of the previous *SnNN*, and the summation $\sum$ layer, which aggregates the output of the previous layers in order to train the model with the aggregated consumption.

The *SNN* layer contains as many *SnNN* as spaces to refrigerate and each *SnNN* is an individual ANN, more specifically a MLP network. From now on, the various MLP networks employed in this structure are named sub-nets to simplify the explanation. These sub-nets, described with the *SnNN* nomenclature, where the *n-th* term defines the sub-net number, pretend to model the behaviour of each S. Each sub-net can have its own number of layers, its own number of neurons, its particular topology and its necessary inputs, $x_{n,i}$, where the *n-th* term defines the sub-net number and the *i-th* term the input number. Therefore, the variety of S characteristics found in an industrial refrigeration system can make the aforementioned configuration of each *SnNN* different. It should be noticed that even though each sub-net can be seen as an individual network, they are trained together with the same aggregated consumption signal as target thanks to the summation layer that connects all the previous outputs.

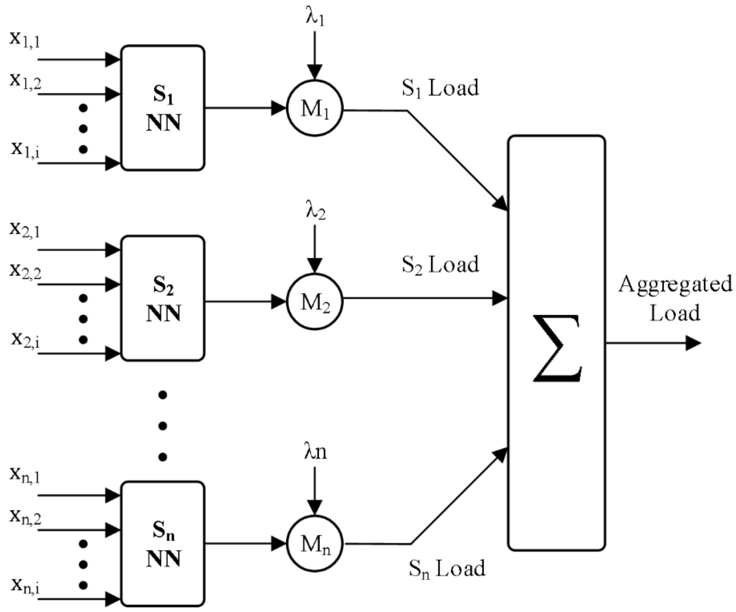



**Fig 5.2.4 - Neural network structure. The first layer, composed by various *SnNN*, contains as many individual *SnNN* as spaces to refrigerate.**

The output of each sub-net is input to the next layer, the multiplication layer *M.* This layer has as many nodes as sub-nets and each *Mn*, where *n-th* stands for the sub-net number, only has three connections. Two inputs, which are the previous sub-net output and the S status, and one output, which is the result of the multiplication of the two inputs. This layer has the functionality to enable or disable the output of each sub-net according to the refrigeration space status (ON/OFF). The refrigeration space status is the signal of the evaporators allocated in each S, in case that the evaporators of a specific S are OFF such sub-net should not contribute to the total consumption. This layer helps the proposed structure to learn the load of each S. On the one hand, it is used to avoid errors in regard to the contribution of each sub-net to the total consumption when it is already known that do suppose any load to the system. And, in the other hand, it is used to bypass the weight updating of its corresponding sub-net in the training phase, fact that only would induce error to the individual S load model.

Finally, the last layer, the summation $\sum$ layer, is used to sum all the previous sub-nets output and generate the aggregated output. Such layer contains as many inputs as sub-nets and a unique output which is the aggregated consumption. Thus, the whole structure is able to be trained simultaneously with the whole consumption signal, $Q$. It should be noticed as well, that the consumption signal $Q$ with which the disaggregation structure is trained, is the cooling capacity of the refrigeration system. This assumption is made considering that all the cooling capacity generated by the refrigeration system is expended to refrigerate the load with no losses in the process. This assumption is made according to the system experts criteria

The mathematical expression of the proposed network structure is presented in **Eq. 5.2.1.6**:

$$Q' = \sum_{n=1}^{N} \boldsymbol{SnNN}(\boldsymbol{w}_n; \boldsymbol{x}_n)(\boldsymbol{\lambda}_n) \qquad \textbf{Eq. 5.2.1.6}$$

where $Q'$ is the estimated aggregated signal, $N$ the number of available *SnNN*, which is the number of spaces to refrigerate ($N$ = number of S = number of sub-nets), $\Phi_i$ ***SnNN*** is the *n-th* sub-net, $\boldsymbol{w}_n$ the *n-th* sub-net weights, $\boldsymbol{x}_n$ the *n-th* sub-net inputs and $\boldsymbol{\lambda}_n$ the *n-th* space to refrigerate status (ON/OFF).

During the training phase, and contrary to traditional disaggregation methods, where each individual load has its target, the weights of the proposed structure are adjusted using the same target signal, the aggregated cooling capacity, $Q$. Moreover, as overviewed before, the training procedure has another particularity to help the structure to estimate the individual consumptions. This characteristic is that the specific weights of each *SnNN* are only updated when the layer *Mn* is activated.

This property provides the possibility to model each space to refrigerate more accurately due to the capability to "switch ON/OFF" each *SnNN* during the training phase, instead of the typical topology where all the weights are updated independently of the refrigerated space state. This particularity of the training phase can be done only with the individual weight update approach. This is because the derivative of the error with respect to the weight of the current sample is zero, therefore, the old weight is maintained as follows **Eq. 5.2.1.7**:

$$^{*}\boldsymbol{w}_n^j = \boldsymbol{w}_n^j - \eta\left(\frac{\partial E(k)}{\partial \boldsymbol{w}_n^j}\right) \qquad \textbf{Eq. 5.2.1.7}$$

with $^{*}\boldsymbol{w}_n^j$ being the new weight of the *j-th* neuron of the *n-th* sub-net and $\boldsymbol{w}_n^j$ representing the old weight of the *j-th* neuron of the *n-th* sub-net. Custom layers such as *Mn* and $\sum$ do not possess weights since their function is only to multiply or sum its inputs respectively.

As aforementioned, each *SnNN* is composed by various layers along with several neurons with their respective activation functions as if it were a common MLP. However, in order to preserve the physical meaning of the modelled magnitude, the load, a singularity to the output layer of each sub-net should be added. This singularity is to force the weight value to be non-negative due as the consumptions cannot be negative in physical terms, for this reason the selected activation function of the neurons is the ReLU. This ensure the positive load of each compartment and forces the network to learn a coherent consumption behaviour.

Finally, once the whole neural network structure is trained, the last layer $\sum$ is deleted and each *SnNN* is able to model by itself each cooling load. Thus, each sub-net can be employed as an individual network with its particular inputs to estimate the load of its representative refrigerated space.

#### *5.2.1.4 Validation with a mathematical simulation of a refrigeration system*

Before validating the complete load management methodology, it is necessary to validate the disaggregation part. The problem is that there is not a straightforward way to measure the cooling load of each S due to the impossibility to install the required instrumentation. Therefore, a mathematical simulation of a refrigeration system is developed in order to test and measure the performance of the proposed disaggregation methodology before applying it in the real system.

The mathematical test bench, explained with detail in the Annex II, emulates the behaviour of the overfeed refrigeration system depicted in **Fig 5.2.5**. It should be noticed that the modelling efforts are focused in the load side of the system, which is composed by the evaporators and its cooling loads. Each space to refrigerate contains different water masses to emulate the cooling load to maintain at a desired temperature. In addition, even though the evaporation and condensation temperature are fixed at the specific system design values, the set points regarding the desired temperature in each space are different. And finally, in order to simulate load inputs and outputs, the water mass in each space is changed randomly. Thus, a simple refrigeration system simulation that mimics the common operation can be used to validate the disaggregation methodology.

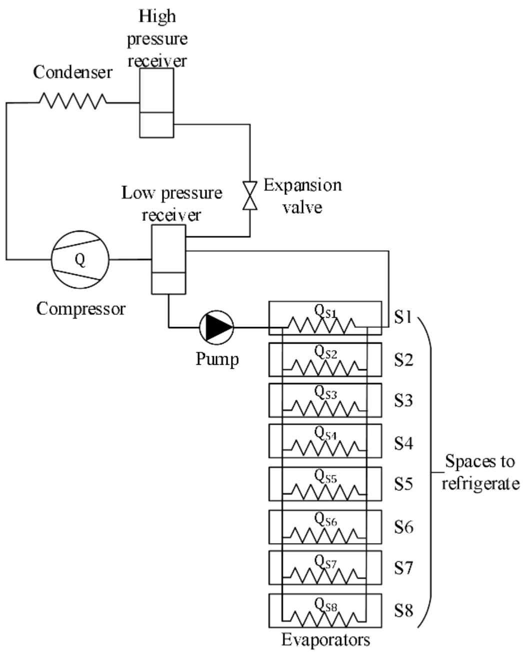



**Fig 5.2.5 - Overfeed refrigeration system with multiple spaces to refrigerate with an evaporator in each space.**

Thanks to the aforementioned mathematical simulation, it is obtained the aggregated cooling capacity signal over the defined simulation time, **Fig 5.2.6 a)**. The purpose of monitoring the aggregated signal $Q$, which is the cooling capacity measured in the compressor, is to mimic the real refrigeration system scenario where is not viable to measure the individual consumptions. Afterwards, taking advantage of the data obtained using the simulation, the contribution of each evaporator, $Q_{S1} - Q_{S8}$, shown in **Fig 5.2.6 b)**, will be used to measure the disaggregation effectiveness. It is assumed that the system has no losses, where the $Q$ measured in the compressor should be equal to the summation of all the loads $Q_{S1} - Q_{S8}$. The signal shape illustrated in **Fig 5.2.6** is due the initial conditions and subsequent stabilization, at the beginning the system start with all the spaces to refrigerate with high temperatures and afterwards they maintain the desired set point within a deadband range.

First of all, the simulation dataset is divided into training and test sets using the first 70% and the last 30% values respectively. The training set is employed to model the behaviour of each space to refrigerate and the test set is used to validate the methodology.

To create the model with the training data, the aforementioned features described in the previous section are developed. All these features are used to feed the proposed neural network structure which parametrization is detailed below. As the simulation contain eight spaces to refrigerate, the proposed NN structure must have eight *SnNN* with its individual topology and configuration. As the purpose of the methodology is to test its viability and is not focused on the parametrization of each sub-net, a grid search and a cross-validation to select the parameters is used.

The grid search parameters are the same for all the *SnNN* to reduce computational complexity, for this reason, all the sub-nets have the same configuration.

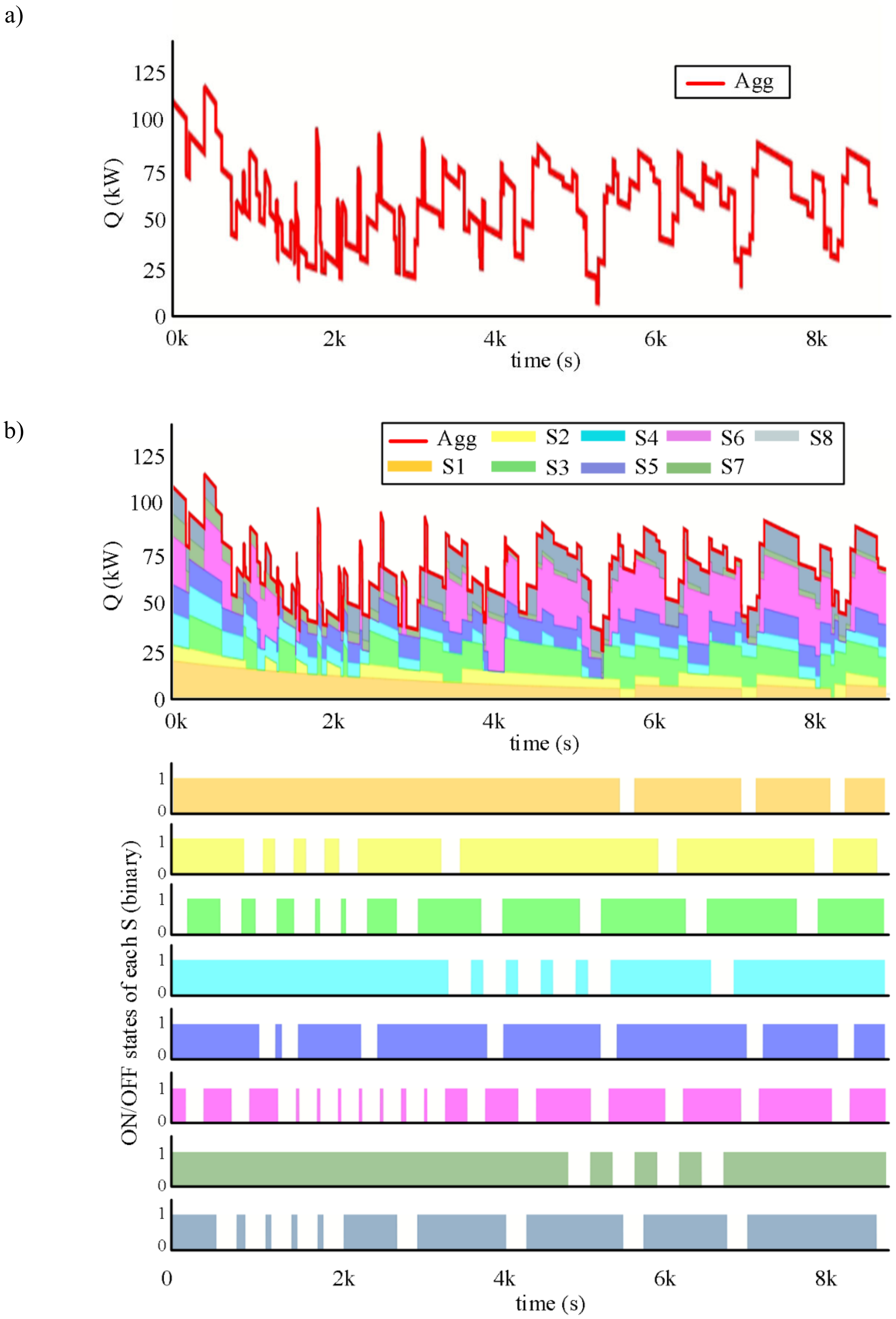



**Fig 5.2.6 - Simulation data. a) Aggregated cooling capacity. b) Disaggregated cooling capacity used by the different spaces (S). Each S has one evaporator. The ON/OFF state of each evaporator is depicted below the stacked consumption.**

The configuration has been adjusted employing the aforementioned methods to avoid overfitting and to ensure a low model error, taking as a loss function the MAE. Using this criteria, each *SnNN* is configured with 2 hidden layers with six neurons each one, one output, and various inputs as depicted in **Fig 5.2.7**. The number of inputs can be different in each *SnNN* depending on the number of evaporators, however, in this simulation, each S only have one evaporator. Moreover, each neuron of each sub-net has a ReLU activation function, this activation function cannot be changed as it is in charge to guarantee that the output is a non-negative value, a fundamental property in order to preserve the physical behaviour. Finally, the learning rate is set to 0.001 and the structure is trained employing the Adam algorithm as optimizer function.

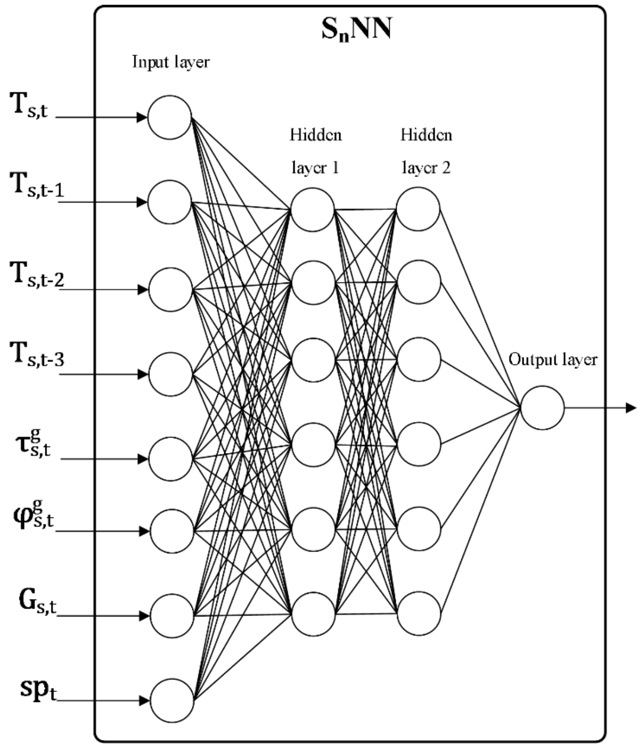



**Fig 5.2.7 - Illustration of a single *SnNN* configuration.**

The subsequent sub-nets outputs are input to its *Mn* layer, along with its evaporator status signal which indicate if its turned ON or OFF. Finally, the sum of all *Mn* outputs is calculated in order to be able to train the network employing the aggregated signal.

Once the model of each space is obtained, the same features are calculated for the test set to be used as inputs in the trained networks. The results of this modelling process are shown in **Fig 5.2.8**, where both the aggregated $Q$ of the test set and the modelled one are depicted. As it can be seen in the figure, the error of this aggregated $Q$ is low, with a MAPE below 0.5% and a MAE below 1kW.

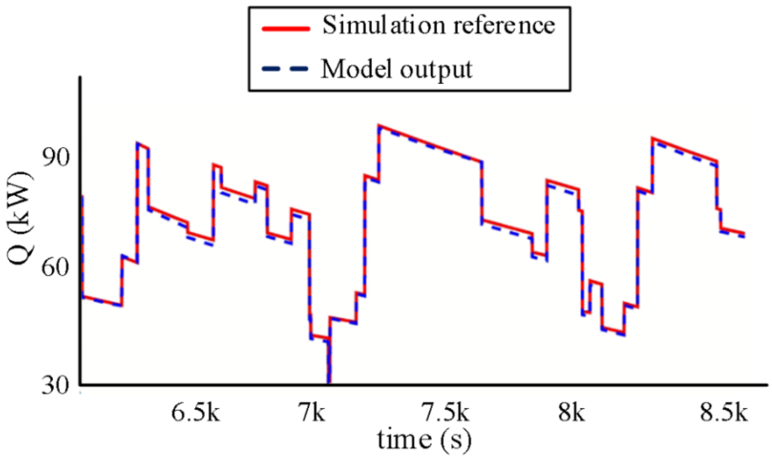



**Fig 5.2.8 - Aggregated test data versus model output.**

However, the main purpose of the methodology is to identify the individual contribution of each S in regard to this aggregated consumption. The output of each sub-net of the specific NN structure created allows to estimate the aforesaid individual consumption. **Fig 5.2.9** depicts the output of the disaggregation algorithm versus the simulation data with the test samples. It is appreciable that even though the different S always work with certain degree of simultaneity in the training set, the methodology is able to distinguish the contribution of each space.

The metrics used to evaluate the performance of the methodology are shown below, in **Table 5.2.2**. The MAPE metric could be used deleting the zeros of the dataset, due to the properties of the *Mn* layer is not possible to commit errors when the evaporator is turned OFF and hence, the zeros do not affect the modelling performance. The perceived errors, although they are minimal, can be attributed to the cooling load of each S, since in the mathematical simulation this value is changed randomly within a determined range. Even though these cooling load values can be input to the disaggregation methodology to reduce the error, they are dismissed since in the real refrigeration system such information cannot be acquired.

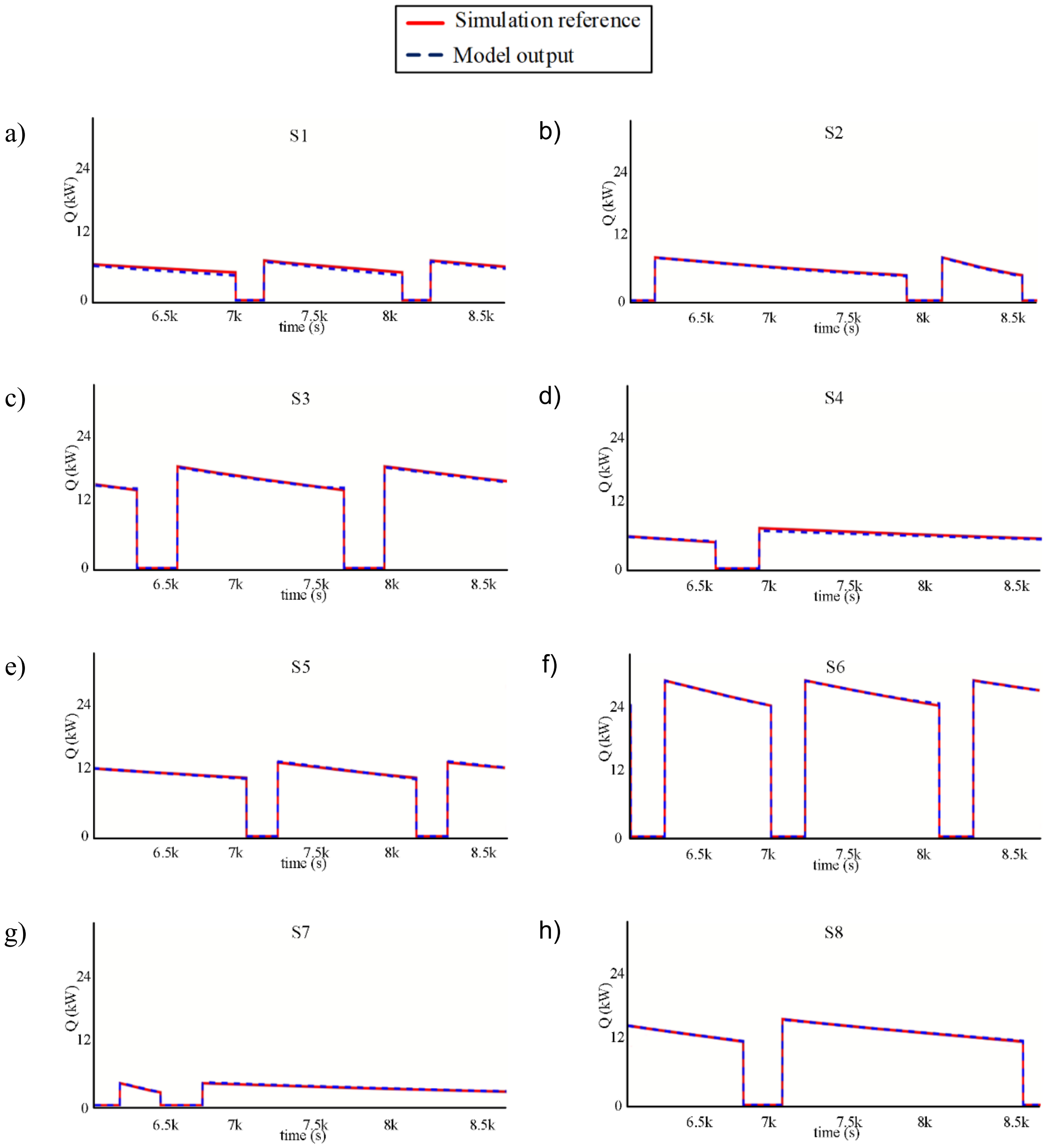



**Fig 5.2.9 - Disaggregation test set outputs. a)-h) single models of each space.**

**Table 5.2.2 - Test set performance metrics of the disaggregation applied simulated refrigeration system.**

| | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | Agg |
|---|---|---|---|---|---|---|---|---|---|
| **MAE(W)** | 0.11 | 0.21 | 0.12 | 0.32 | 0.25 | 0.11 | 0.17 | 0.72 | 0.81 |
| **MAPE(%)** | 3.69 | 4.46 | 1.07 | 5.87 | 2.67 | 0.54 | 6.11 | 0.66 | 0.49 |

### 5.2.2 Load balancing strategy

Load balancing is a term referred to the capability to shift or shed the loads in order to avoid undesired consumption peaks. To achieve such goal, most of energy systems require different types of storage technologies in order to mitigate high simultaneity consumptions. In refrigeration, the spaces to be refrigerated can be used themselves as energy storages using its intrinsic capability to reject and absorb heat. This aspect opens a wide variety of approaches to tackle such load balancing issue taking advantage of such property.

However, industrial refrigeration processes often require a specific amount of energy to maintain its products under specific conditions, no more no less. Hereby, in most scenarios the temperature range cannot be surpassed, forcing to preserve the products and the processes under specific temperature thresholds, limiting the storage capabilities of the system. Taking into account this constrain and the incapacity to schedule the different parallel processes to refrigerate, due to production restrictions, a real-time methodology is proposed to preserve the product conditions. The methodology takes advantage of the disaggregated data and the system signals to smooth the consumption shape, thus increasing the compressors efficiency. Therefore, the same feature engineering step as the one explained in the load disaggregation section needs to be performed in order to obtain the consumption of each S.

Moreover, in this real scenario, each S contains various evaporators of the same characteristics. Thus, the total $Q$ of each S is divided by the number of evaporators in order to estimate the contribution of each one. This is done since the proposed balancing strategy is performed acting on the evaporators individually. Such balancing problem tackled in this section is detailed below.

#### *5.2.2.1 Optimization problem formulation*

Knowing the consumption of each evaporator of the case study thanks to the disaggregation, and being aware of the operation restrictions in order to maintain the product quality, a mathematical optimization problem arises to smooth the load curve and mitigate the peaks while preserving the compressors in efficient partial loads. The optimization algorithm can be approached as an integer non-linear problem with the objective to find the best number of evaporators turned ON in each S in order to minimize the consumption variability **Eq. 5.2.2.1**.

$$argmin_{\{G\}}(Q_t - Q'_{t+1}) \qquad \textbf{Eq. 5.2.2.1}$$

, where

$$Q'_{t+1} = \sum_{n=1}^{N} G_{n,t+1} \times \hat{Q}_{n,t+1} \qquad \textbf{Eq. 5.2.2.2}$$

Being $\hat{Q}$ the cooling load consumed by an evaporator obtained with the disaggregation consumption model, $N$ the number of spaces to refrigerate, where ($N$= number of S), and $G$ the number of active evaporators.

The number of active evaporators in a space to refrigerate is modified according to a labelling strategy. Each space evaluates the necessity of $Q$ to preserve the set point conditions, thus, some of the spaces to refrigerate are forced to "upgrade" or "downgrade" by means of starting or stopping evaporators. Otherwise, if the space to refrigerate is within its deadband, labelled as "free", the optimization solver can choose the number of evaporators that minimizes the function. Mathematically speaking, such labels are described as bounds in in the $G$ selection:

$$U_s = \begin{cases} \min(G_{n,t+1} + 1,\ B_n), & (\varepsilon_{n,t} < h_n^1) \vee \left((\varepsilon_{n,t} < h_n^2) \wedge (\Delta T_{n,t} < h_n^3)\right) \\ \max\left(G_{n,t+1} - 1, 0\right), & (\varepsilon_{s,t} > h_s^4) \vee \left((\varepsilon_{n,t} > h_n^5) \wedge (\Delta T_{n,t} > h_n^6)\right) \\ B_n, & otherwise \end{cases} \quad \textbf{Eq. 5.2.2.3}$$

$$L_s = \begin{cases} \min(G_{n,t+1} + 1,\ B_n), & (\varepsilon_{n,t} < h_n^1) \vee \left((\varepsilon_{n,t} < h_n^2) \wedge (\Delta T_{n,t} < h_n^3)\right) \\ \max\left(G_{n,t+1} - 1, 0\right), & (\varepsilon_{n,t} > h_n^4) \vee \left((\varepsilon_{n,t} > h_n^5) \wedge (\Delta T_{n,t} > h_n^6)\right) \\ 0, & otherwise \end{cases} \quad \textbf{Eq. 5.2.2.4}$$

In the displayed boundary functions **Eq. 5.2.2.3** and **Eq. 5.2.2.4**, $U$ and $L$ refer to the upper and lower boundaries respectively and $B$ is the max amount of available evaporators. The multiple $h$ are the fixed thresholds selected using each space to refrigerate deadband and cooling necessities. Finally, $\varepsilon_{T,n}$ is the temperature ($T_n$) error regarding the set point ($TSP_n$) displayed in **Eq. 5.2.2.5** and $\Delta T$ is the temperature difference among two consecutive timesteps, **Eq. 5.2.2.6**.

$$\varepsilon_{T,n,t} = \left(T_{n,t} - TSP_{n,t}\right) \quad \textbf{Eq. 5.2.2.5}$$

$$\Delta T_{n,t} = (T_{n,t-1} - T_{n,t}) \quad \textbf{Eq. 5.2.2.6}$$

As the formulated optimization problem is non-linear, a little trick is performed in order to transform it to linear and reduce its complexity, and hence, its computation time [161]. The trick consists in divide the problem into two linear optimization problems shown in **Eq. 5.2.2.7** and **Eq. 5.2.2.8**:

$$argmin_{\{G\}}(Q_t - Q'_{t+1}) \geq 0 \quad \textbf{Eq. 5.2.2.7}$$

$$argmin_{\{G\}}(Q'_{t+1} - Q_t) \geq 0 \quad \textbf{Eq. 5.2.2.8}$$

Finally, the lowest of the two solutions is selected in order to recommend the number of evaporators in each space.

## 5.3 Experimental results

In this section, the whole load management methodology is validated in the real refrigeration system, including the disaggregation and the load balancing as well.

### 5.3.1 Load disaggregation

Having ensured the viability and performance of the disaggregation methodology in a simulated environment in the previous section, the next step is to move the experimental tests into the real refrigeration system. The real system detailed in Annex I is composed of 8 spaces to refrigerate, as in the simulated experiment, with the particularity that different number of evaporators are located in each space. Nevertheless, all the evaporators within the same space are identical, which means that the cooling capacity expended by each one can be easily obtained dividing the Q of that S by the number of evaporators, and assuming an ideal evaporators condition. In addition, in this scenario, it is also considered that the $Q$ provided by the compressors is the $Q$ expended by the evaporators, considering no losses in the circuit, assumption made according with the system experts opinion.

In this real test, the used neural network structure is the same as in the mathematical simulation with slight variations due to the various evaporators installed in each S. In this case, the aggregated cooling capacity signal provided by the refrigeration system, shown in **Fig 5.3.1**, is obtained using a flow meter installed in the system. However, in this scenario, it is not possible to measure the performance of each disaggregated model due to the lack of instrumentation, and the evaluation should be done with the aggregated signal only. Further details of the training and the parameters configuration of this experimental validation are explained below.

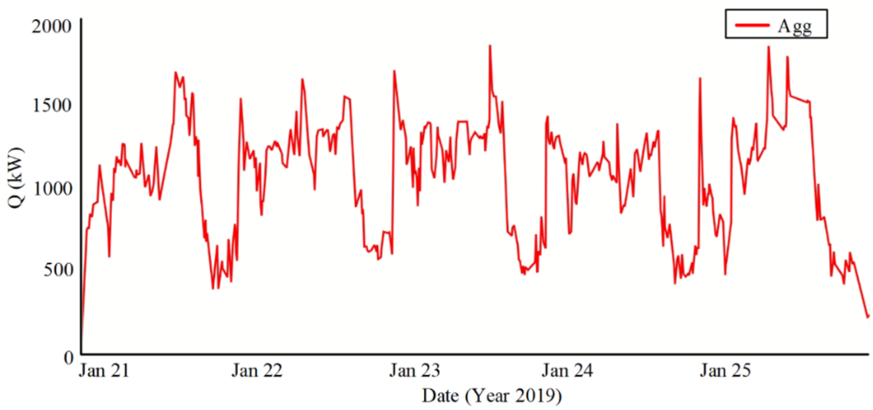



**Fig 5.3.1 - Detail of the refrigeration system cooling capacity in a common week.**

To train the proposed disaggregation methodology, a dataset acquired from a whole year operation of the real refrigeration system is split in 2 parts, the training and the test sets, with 75% and 25% of data respectively. For this splitting, the same strategy of the performance assessment is employed, where 3 weeks every 4 weeks are selected as train and the remaining to test. This is done to obtain a representative partition as the cooling load can be affected by cyclical production and consumers' behaviours, which was not the case of the simulated experiment where the split was performed sequentially.

To begin with the test, the same features as in the simulation example are calculated, with the particularity that, in this real case study, more variables are input into each *SnNN* due to the multiple evaporators allocated in the same space to refrigerate. Such variables are the ones related with the individual evaporators operation: $\tau^{g}_{s,t}$ and $\varphi^{g}_{s,t}$. In addition, the *Mn* layer, which is in charge to determine if a S is expending energy or not, is performed with a logical OR of the multiple evaporators status, ON/OFF.

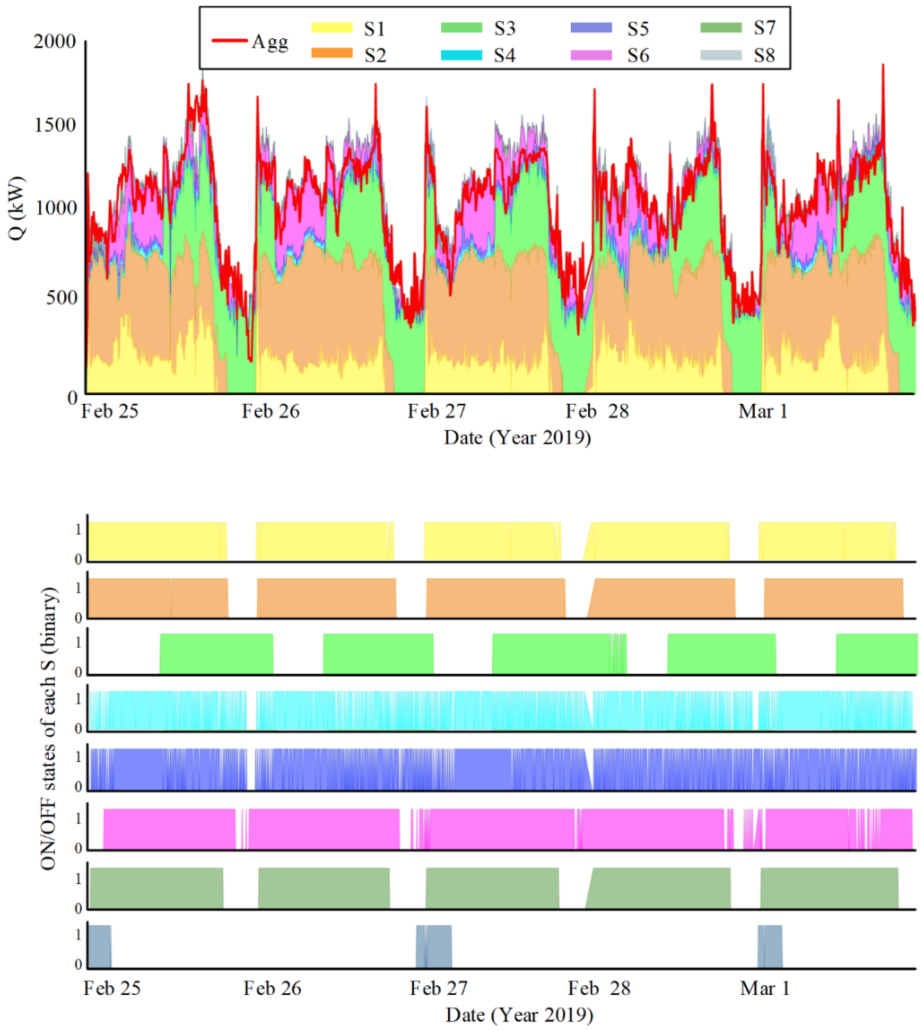
For this experimental validation, the proposed NN structure contains 8 *SnNN*, one for each S, and the configuration selection of each sub-net is performed as in the mathematical simulation, **Fig 5.2.7**.In this case, such configuration is composed by 2 hidden layers with 8 neurons each one, a ReLU activation function, an Adam optimizer and a value of 0.001 for the learning rate. As in the mathematical simulation, the configuration is chosen employing a grid search with various parameters and cross-validation, then, the parametrization with lowest MAE is chosen.

Finally, with the NN structure configured, the training set is used to develop the model of each S, and the test set is employed to validate the effectiveness of the methodology although in this scenario there is only the aggregated $Q$ to validate the performance. However, it should be noticed that the disaggregated loads obtained are coherent according to the system experts opinion considering the different processes and evaporators installed in each S.

**Fig 5.3.2 a)** depicts how the method distributes the load among the different spaces to refrigerate with its respective S status. As aforesaid, these statuses are calculated with logical OR of the different evaporators operation allocated in the same S. Such statuses behaviour is quite different depending on the type of process that is developed in each S.

In this real scenario, the performance of the disaggregation can be only evaluated with the aggregated signal due to the high simultaneity and lack of instrumentation. In **Fig 5.3.2 b)** the difference between the aggregated test data and the aggregated model output is depicted, obtaining a 108.76kW of MAE and a 12.61% of MAPE. These errors are higher than ones of the simulation, some of them, as in the mathematical simulation, can be attributed to the lack of cooling load data. Most of the processes done in each S have an irregular behaviour regarding its load, which induces variability hard to learn by the model without any information. Additionally, the dataset employed contains periods where some evaporators were disconnected due to maintenance issues and the database do not reflect it. In this situation, the dataset reflects variables of the evaporators that do not match with the real evaporator state since the PLC continued operating as usual. Therefore, the variables input to the NN structure are not always trustworthy, causing additional training errors.

a)




b)

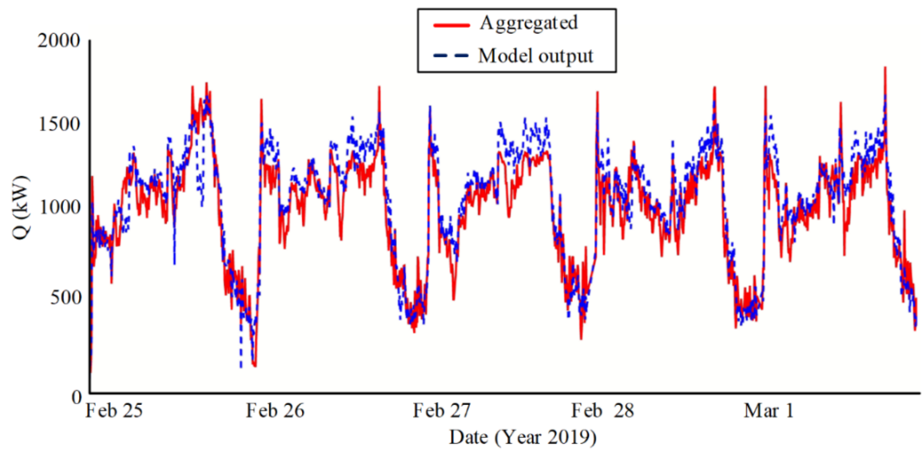



**Fig 5.3.2 – Disaggregation output detail of a week from the test dataset. a) Real aggregated consumption compared with the stacked individual consumptions. Note that the slopes seen in the ON/OFF plots are due to periods where interpolations are done due missing data. b) Real aggregated consumption versus estimated.**

Despite the S simultaneity is really high as it can be seen in **Fig 5.3.2 a)** with the ON/OFF operation, there are certain situations during the year where the S3 is working alone. Hence, in such situations, it is possible to compare the disaggregated value of the methodology with the $Q$, which should be the same as there is only this S operating. In the test dataset, there is a period that occurs the aforementioned situation. The **Fig 5.3.3** depicts the scenario with only the S3 operating, and it is appreciable that the disaggregation can follow the consumption dynamics despite the lack of cooling load data and the aforementioned maintenance issues of the dataset. The measured results with the MAE and the MAPE are 47.54kW and 12.80% respectively, which agree with the aggregated results indicating that the disaggregation is trustworthy.

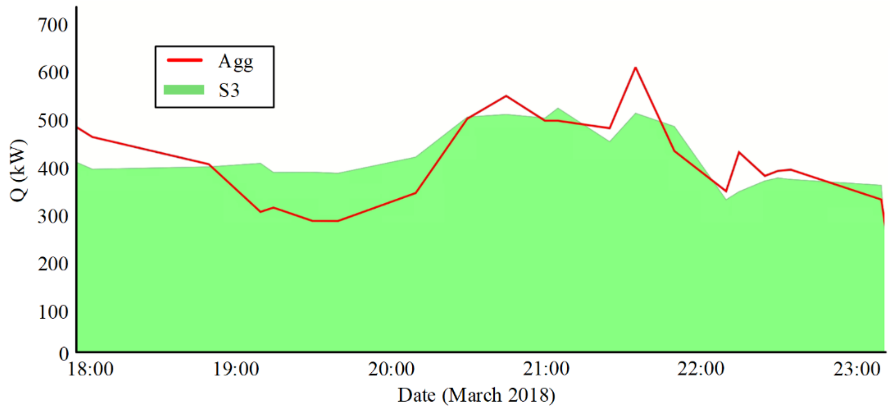



**Fig 5.3.3 - Detail of a specific period in the test data where only one S was operating.**

In addition, should be noted that the disaggregated signals obtained are coherent according to the system experts due to the different processes and evaporators installed in each space to refrigerate.

### 5.3.2 Load balancing

The next step is to take advantage of these disaggregated models to balance the load of the system to increase its performance. The proposed strategy uses the cooling deadband of the spaces to refrigerate, along with the estimated consumption of each one, to develop a real-time load smoothing. The goal, as explained in the previous Section 5.2.2 with the relevant equations, is to minimize the peaks avoiding unnecessary compressors switching and increase the efficiency by means of the load management.

First of all, employing the models obtained from the disaggregation step and acquiring real-time data from the system with its subsequent feature engineering part, the consumption of each evaporator in each refrigerated space is estimated. It is assumed that the various evaporators of the same space contribute in the same way to the cooling expenditure, so the total consumption of a space can be divided by the current number of evaporators turned on to know the individual expenditure of any evaporator. It should be noticed that aging and degradation that affect the performance of evaporators have not been considered in this study.

Afterwards, each space to refrigerate is labelled with a certain tag depending on its temperature requirements. These labels are expressed in the boundary equations of the optimization problem, formulated in the methodology description, **Eq. 5.2.2.3** and **Eq. 5.2.2.4**. The multiple $h$ parameters of such equations, since can influence the operation of each S, are selected according to the system experts' opinion. Basically, the tags assigned in each space are used to force an upgrade, which means an increase of cooling turning on more evaporators, or a downgrade, which demands a decrease of the cooling capacity turning off some evaporators. In the case that the space is in the desired temperature range, which can be labelled as free, the optimization algorithm can choose the number of evaporators in order to avoid the consumption peaks.

In practice, some management rules have been integrated: the upgrade label is forced to be at maximum of one evaporator if they are not all already on, and the downgrade is forced to be at maximum of one evaporator also, if they are not all already off. These constraints are employed to diminish the abrupt changes in cooling capacity and temperatures. In addition, the refrigerated spaces which are not constrained with the upgrade or downgrade labels are also limited regarding the number of evaporators. The maximum modification respecting the current number of evaporators is limited to two evaporators for the same reason as in the other labels. These measures are performed according to the methodology goals and with the advice of the refrigeration system experts.

At this point of the methodology, the optimization problem presented in **Eq. 5.2.2.1** is solved by means of the default CBC solver of the PuLP library provided by [162]. Due to the online nature of the load balancing approach, and without the necessity to train the methodology as the disaggregation should be already trained, the proposed method is validated directly to the refrigeration system. For this reason, the load management methodology is validated in real-time in the refrigeration system within 8 consecutive days of operation. The gap among the two working weeks is due to the Eastern holidays.

To be able to compare it and validate its improvement capabilities in regard to the compressors performance, each validation day of operation is compared with a reference day. The reference day is the most similar day taking into account the suction pressure, discharge pressure and cooling capacity of the available historical dataset, which are the variables that affect the compressor performance as already explained in previous chapters.

In this regard, **Table 5.3.1** shows the values of the variables from the tested day with the proposed method against the values of the day used as a reference. As it can be seen in the table, no huge differences in the variables values can be found between both days, the tested and the reference, and hence, a realistic evaluation can be made.

**Table 5.3.1 - Comparison between the variables of validation days and reference days.**

| Proposed | | | | Reference | | | |
|---|---|---|---|---|---|---|---|
| Date | *Q* (kWh) | Suction P (bar) | Discharge P (bar) | Date | *Q* (kWh) | Suction P (bar) | Discharge P (bar) |
| **2020-04-06** | 29518 | 1.70 | 8.01 | 2020-01-21 | 28673 | 1.70 | 8.03 |
| **2020-04-07** | 28101 | 1.69 | 8.02 | 2020-01-21 | 28673 | 1.70 | 8.03 |
| **2020-04-08** | 30066 | 1.69 | 8.03 | 2019-10-17 | 30270 | 1.72 | 8.09 |
| **2020-04-09** | 23099 | 1.78 | 8.00 | 2019-12-27 | 23263 | 1.71 | 8.00 |
| **2020-04-14** | 35380 | 1.70 | 8.32 | 2019-06-19 | 31580 | 1.67 | 8.76 |
| **2020-04-15** | 31948 | 1.71 | 8.35 | 2019-10-17 | 30270 | 1.72 | 8.09 |
| **2020-04-16** | 33575 | 1.70 | 8.63 | 2019-06-19 | 31580 | 1.67 | 8.76 |
| **2020-04-17** | 30264 | 1.70 | 8.59 | 2019-08-13 | 30175 | 1.70 | 8.70 |

The results of the load management methodology aim to reduce the undesirable consumption peaks and increase the efficiency of the compressors by maintaining its PLR in the optimal zone. Note that the validation of the impact of such load management strategies is not common in the literature. For this reason, two different scores have been used in order to quantify the impact of the proposed methodology. These scores are the simultaneity coefficient, and the time that the compressors are operating in high efficiency PLRs. Therefore, the validation of the proposed methodology proceeds with these two scores.

First of all, to measure the consumption peaks, the simultaneity coefficient is calculated. This simultaneity coefficient measures, in minutes, how much time two compressors have been working in parallel. This is a key parameter that should be minimized, since worst performances are achieved when the refrigeration system is operating with two compressors in parallel in situations where are not required.

This metric is used as follows, in most scenarios this simultaneity happens when a peak occurs and a second compressor is needed to supply the demand necessities, e.g. situations where a new refrigerated space is turned on or some load is input to a refrigerated space and force the operation of multiple evaporators in parallel. After these situations, and due to compressors constraints, even the peak has already passed and the second compressor is no further needed, it remains operative to minimize the starts and stops, leading to a poor performance operation. The load balancing should smooth the load avoiding these peaks and therefore, reduce the simultaneity time where the system operates with two compressors.

**Fig 5.3.4** illustrates the effects of the proposed load management methodology measured with the simultaneity metric. As it can be appreciated in the figure, the proposed methodology spends less time with two compressors than the reference days, which means less simultaneity. During the tested days a substantial reduction of about 438 minutes of the second compressor operation per day is achieved, which means a reduction of about the 77% of simultaneity in regard to the reference.

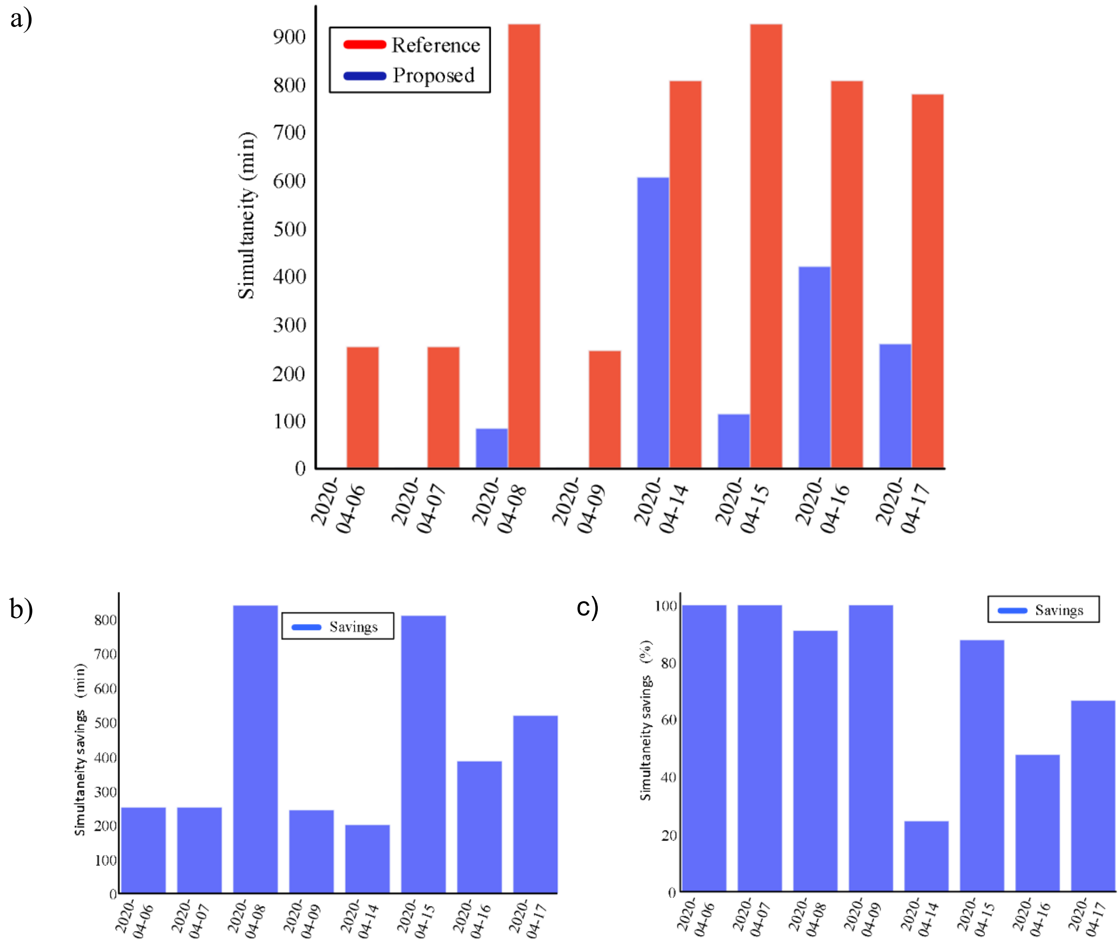



**Fig 5.3.4 - Simultaneity results. a) Simultaneity of the proposed method compared with the reference. b) Minutes saved with the proposed method vs reference. c) Percentage of simultaneity that it supposes.**

Secondly, to measure the compressors performance, the PLR is directly employed. As shown in previous chapters, the compressors efficiency is highly related with its partial load. Higher partial loads mean higher efficiencies, hence, the PLR is used to measure the compressors efficiency. The metric is formulated as in **Eq. 5.3.2.1**, which measures the percentage of time per day that the compressors were operating above 90% of its PLR ($\rho_{day}$):

$$\rho_{day} = \frac{(t_{C1}^{>90} + t_{C2}^{>90}) \times 100}{t_{C1}^{ON} + t_{C2}^{ON}} \qquad \textbf{Eq. 5.3.2.1}$$

Being $t_{C1}^{ON}$ and $t_{C2}^{ON}$ the operating time per day of compressors one and two respectively in minutes and $t_{C1}^{>90}$ and $t_{C2}^{>90}$ the operating time above the 90% of PLR per day of compressors one and two respectively in minutes.

From **Fig 5.3.5** it is observable that during the working days tested with the proposed methodology, the compressors operate more percentage of the time with high PLRs. The mean $\rho_{day}$ of the proposed solution is about 63% while the reference is about 46%, that means an increment of about 17% of time working in a more efficient PLR conditions.

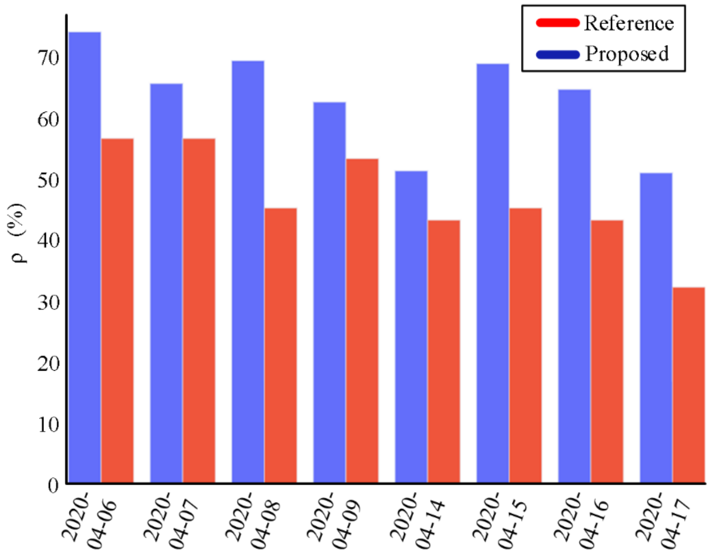



**Fig 5.3.5 – Compressor efficiency results. Comparison of percentage of time in high efficiency PLR.**

With these two measurements it is noticeable that the proposed methodology reduces the time with two compressors operating in parallel and increases the efficiency of each compressor while they are operating. Once validated these two aspects, the **Fig 5.3.6** illustrates how this methodology affects the consumption in terms of electricity expenditure, which is the main goal in order to be more efficient and save energy.

With this **Fig 5.3.6** the methodology demonstrates its effectivity reducing the energy expenditure of the compressors. Managing the evaporators of the system, hence the load, the compressors reduced its consumption per day about 1600kWh which means a reduction of about a 17% compared with the reference days.

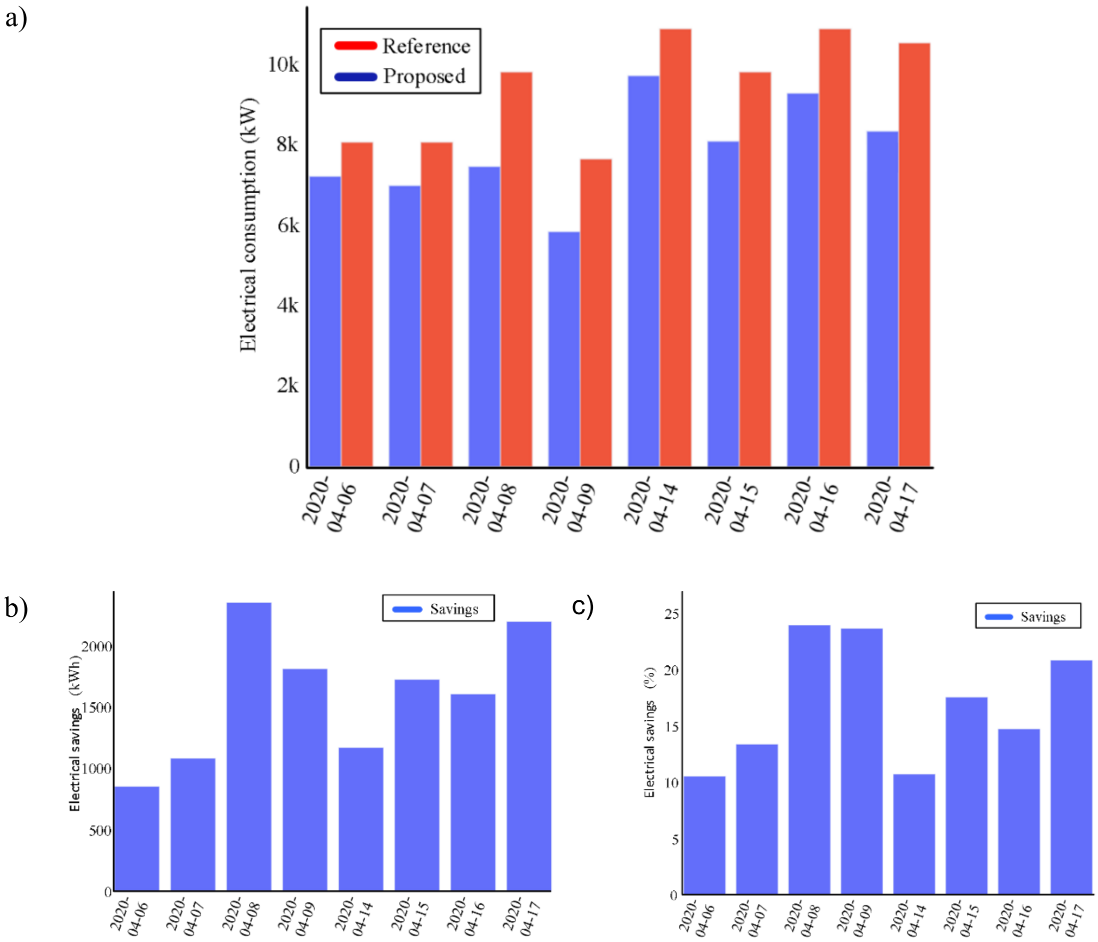



**Fig 5.3.6 - Electrical consumption results. a) Electrical energy consumption of the proposed method compared with the reference. b) Energy saved with the proposed method vs reference. c) Percentage of energy that it supposes.**

An accumulative plot of the savings is presented in **Fig 5.3.7**, both for the electrical energy savings and the operation time of the compressors. During the tested days, a steep trend is shown in both plots. Taking into account these 8 tested days, the methodology is able to save about 12800kWh of electrical energy and 3500 minutes of compressors operation. Extrapolating these numbers to a whole year of operation, and assuming that the savings are constant among the different periods of the year, they suppose about 420MWh saved. These savings equal to the annual consumption of about 129 households in Spain and 167700kg of $CO_2$ according to Red Eléctrica de España.

a)

b)

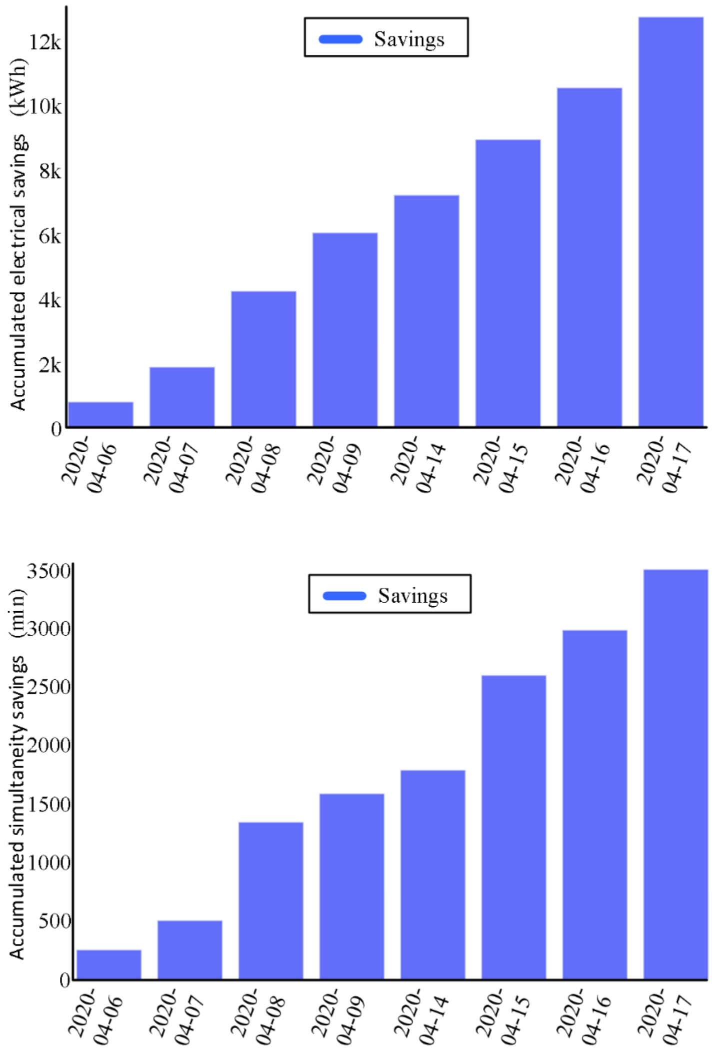



**Fig 5.3.7 - Accumulated savings. a) Electrical energy. b) Time of simultaneity operation.**

The aforementioned improvement in performance terms of the proposed methodology is validated with the previous metrics. It is confirmed that the load management affects the compressors operation, since that they are able to supply the same $Q$ with the expenditure of less electrical power.

However, to fully ensure the effectiveness of the methodology, it is necessary to ensure that the temperature set points of each space to refrigerate are correctly maintained. There is no use in reduce the energy expenditure if the desired objective, which is the proper refrigeration of the products, is not achieved. **Fig 5.3.8** depicts the temperature error of each day in each space to refrigerate. According to experts, and following the historical control rules, each set point has 2 degrees of deadband, one above and one below the set point, where the temperature error is admissible.

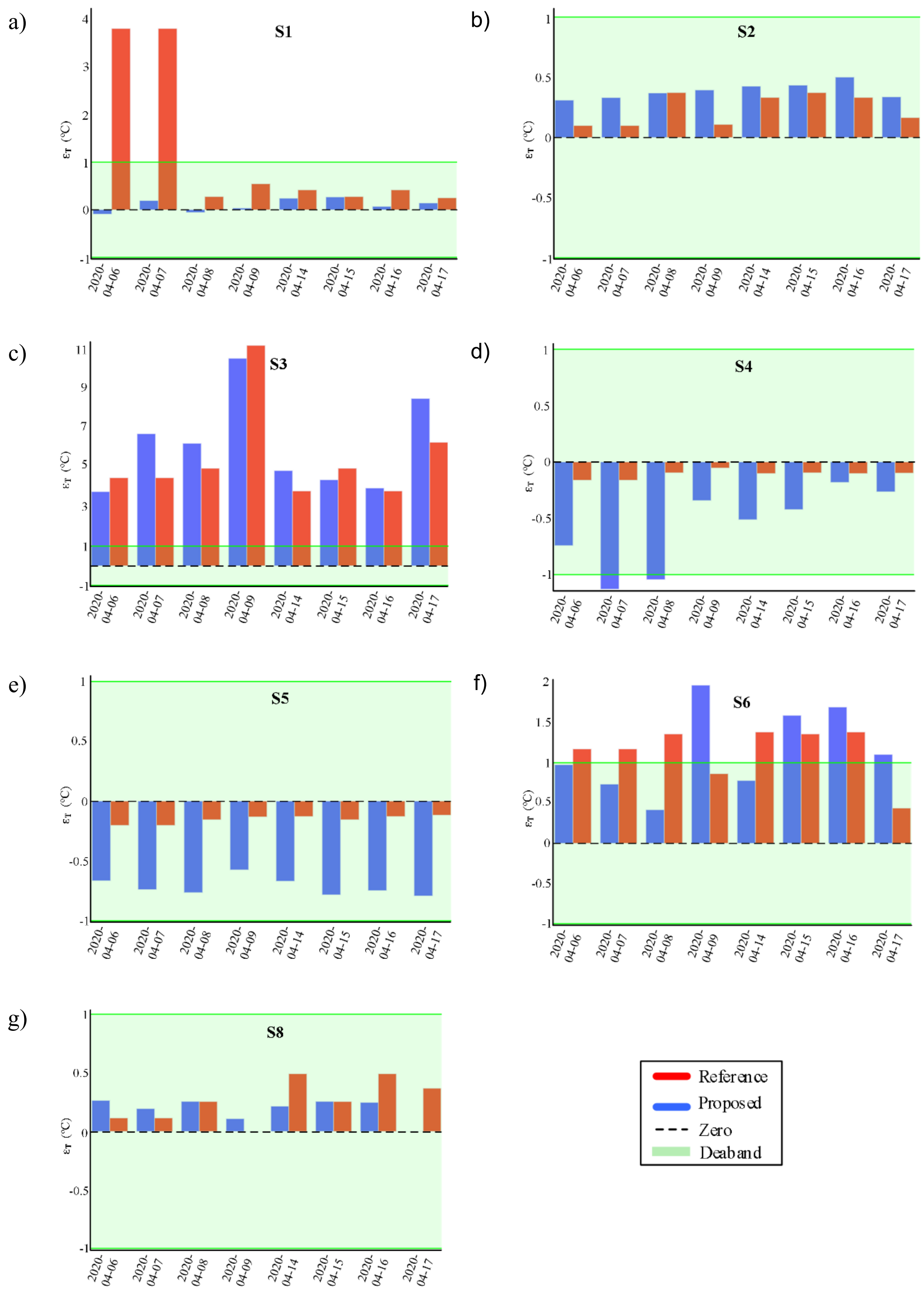



**Fig 5.3.8 – Temperature error in regard to its set point of the different spaces to refrigerate. a)-g) Error in each space.**

The **Fig 5.3.8** demonstrates that the temperature errors of the proposed load management methodology are similar to those of the historical control. Most of the spaces to refrigerate are within its deadband except the S3 which is totally outside, both with the proposed method and with the historical one. As depicted in **Fig 5.3.2 a)**, in the ON/OFF states, the evaporators of the aforementioned S3 are always ON. This means that even though the evaporators are constantly operating, this space cannot be refrigerated to the desired temperature. In this scenario, more evaporators should be installed or the current ones should be substituted with more powerful ones in order to achieve the desired temperature. A similar situation happens with the S6, however, in this space the cooling requirements cannot be achieved only in certain periods, when the load in the space is higher. For this reason, the temperatures, both in the proposed and the reference days, are slightly higher than the desired deadband.

In addition, note that S4 and S5, although being in the green zone, they tend to be overcooled. The management methodology uses them as a cooling battery to smooth the demand, since they are usually labelled with the free tag. This can be done as the evaporators of these spaces are oversized. **Fig 5.3.2 a)** depicts the constant switching actions of their evaporators, while in other S there are at least one evaporator turned ON in order to maintain the temperature. Furthermore, it should be mentioned that S7 does not appear in the evaluation, since this space has its own control which cannot be managed by the system control.

These presented experimental results, allow to validate the capability of the methodology to increase the compressors operation efficiency while maintaining the temperature as well as with the historical control.

## 5.4 Conclusions and discussion

This chapter has demonstrated that the load management is an effective indirect approach to increase the efficiency of the refrigeration system compressors. The necessity to identify the individual consumption of each cooling load is tackled by means of a novel neural network structure. Whereas the system improvement in terms of efficiency is approached using a load balancing strategy suitable for stochastic load behaviour.

In industrial refrigeration systems, the instrumentation needed to measure the cooling load of each space to refrigerate is extremely expensive. For this reason, a NILM approach to disaggregate the individual loads from the whole consumption signal is presented. The methodology does not add any economic cost to the system as it takes advantage of the already acquired system signals. Moreover, contrary to most of the current state of the art NILM strategies, which are applied to electrical loads and require previously labelled data, the proposed neural network structure does not need any kind of labelling, which also minimized the work load of the system experts.

On the other hand, a robust load management should be proposed in industrial environments where the temperature of the products is of vital importance in order to preserve its quality. Due this concern, and the impossibility to manage the schedule of the different processes, the load balancing strategy presented does not assume any future behaviour of the system load. Thus, the methodology is able to preserve the products within the desired temperature while smoothing the load shape. That fact, reduces inefficient load peaks with its associated harmful compressors switching, and force the compressors to operate with a more optimal PLRs.

The innovative qualities presented in this chapter can be used in any industrial refrigeration system to be aware of the amount of cooling capacity expended by each one of its spaces to refrigerate, and to reduce the electrical energy expenditure as well.

Finally, the experimental results presented, illustrate the effectiveness and the robustness of the presented methodology. In regard to the disaggregation results, the mathematical simulation validates the capability of the proposed neural network structure to estimate, with high accuracy, the individual consumption of each space even though the high simultaneity among the different loads. In addition, the tests developed in the industrial system bear out its effectiveness in a real environment.

About the entire load management, which includes the disaggregation and the load balancing, its capability to increase the system performance is demonstrated via the experimental tests applied in the industrial refrigeration system. Such promising results depict the increase in system efficiency, reducing the simultaneity time with various compressors in parallel and reducing the electrical consumption while preserving the product temperature constraints. The simultaneity savings can also be beneficial in maintenance, since the compressors operate less hours and hence, the scheduled preventive tasks are less frequent. Moreover, since the compressors operation is reduced, less failures may occur, which minimize the probability of unexpected downtimes. Such results represent a significant improvement that points out the necessity of performing a proper management of loads in an industrial refrigeration system.

Lastly, it should be mentioned that the potential savings of the presented load management can be incremented combining this methodology with the compressors PLR set point recommendation of the Chapter 4. Thus, the load management guarantees the minimum time with two compressors operating in parallel, and the set point recommendation guarantees a near-optimal generation of the required cooling capacity.

6.

## Conclusions and future work

This chapter outlines the major conclusions of the performed research as well as the promising paths to continue the study.

CONTENTS:

# 6 Conclusions and future work

## 6.1 Conclusions

This thesis presents a data-driven energy management framework, with the purpose to increase the efficiency of the refrigeration systems. Such objective is achieved considering the three main aspects in order to improve an energy system: the performance assessment, the operation improvement and the load management. The conclusions drawn in this section take into account the relationship between the stated hypothesis, the main objectives and the innovative contributions of each one of the main aspects, aspects that correspond to the Chapters 3, 4 and 5 of this thesis. A list of the main contributions and its conclusions is presented below:

- A reliable performance benchmark able to assess the performance considering different operation conditions.
- A robust assessment that deals with non-previously seen or poorly represented operation conditions.
- An assessment capable to create new performance scenarios within each operation condition.
- A fast PLR set point recommendation based on historical data and considering the system operation conditions.
- A PLR recommendation that considers the consumption trend and preserves the system constraints.
- A novel disaggregation technique for cooling loads that only use the monitored variables.
- A robust and reliable load balancing technique that takes advantage of the disaggregated loads.

### *Performance assessment*

The first aspect makes reference to the performance assessment, a fundamental part in any energy management approach in order to identify the system efficiency and the improvement capabilities. In this regard, one key property of such methodologies is reliability. A reliable assessment should consider the different variables that affect the system efficiency, deal with atypical or new data to provide a robust measurement and overcome the bias induced by historical management strategies. For this reason, this thesis has made various contributions in regard these assumptions in order to achieve a robust and trustworthy performance assessment.

***A reliable performance benchmark able to assess the performance considering different operation conditions.***

The first step to assess is to create a benchmark in order to compare the evaluated system. To do so, the proposed methodology employs a SOM with multiple variables to create an operation grid of the compressors. Each discretized area of the grid describes a particular set of operation conditions, where the best historical performance can be used as a benchmark. Therefore, the performance assessment contemplates various compressors and its affecting variables in order to create such benchmark.

Concerning to this benchmark operation grid, the most critical aspect is the amount of input space that each neuron of the grid covers. Such neurons should describe a portion of the space with relatively similar operation conditions in order to preserve the physical meaning. A high number of neurons covering the same space would cause an overfitting issue that vastly reduce the generalisation and proliferation capabilities of the benchmark. This is due to the reduced subset of samples that a neuron would represent. A reduced number of neurons would produce sparsity problems, leading to poor resolution of the operation conditions space. Such scenario would reduce the benchmark reliability as the near-optimal COP samples of each discretized area would be obtained from different operation conditions, losing all the physical resemblance and the capability to perform the proliferation in a trustworthy manner.

Moreover, to be able to assess the performance of a new sample, its operation conditions should be as similar as possible to its representative neuron. Therefore, in situations where the input space of the SOM is not properly discretized, most of the samples would not be well described disabling the comparison reliability.

The aforementioned issue does not have a predefined solution as the different number of neurons or the different number of cooling capacity segmentations to perform the proliferation should be selected according to the specific problem and dataset. Such discretization should consider factors as the dimensionality of the operation space, the amount of available data and always considering the preservation of the physical meaning.

***A robust assessment that deals with non-previously seen or poorly represented operation conditions.***

The proposed assessment provides a robust measurement using an outlier detection algorithm combined with an uncertainty metric in order to label the assessment reliability. Such technique allows to identify poorly represented or not previously seen operation conditions, which indicates that the assessment is not trustworthy. Situation, that if it is maintained during significant amount of time, can also be used as a fault indicator.

It has been proved in the thesis that the management of the model information is crucial in terms of robustness of the assessment. In this regard, the inclusion of two different outlier detection tools in two parts of the methodology is a novel approach conducted in this thesis.

On the one hand, the first outlier detection, which is only performed in the grid creation, allows to split the dataset into the known data and outlier data. Such approach brings the possibility to create the benchmark operation grid using only the known data. That premise reduces the problems of sparsity in regard to the neurons distribution, provides an abnormal operation dataset for the uncertainty delimitation and reduces computational burden in the online evaluation. Such outlier dataset selection should be done in regard to the data distribution as each problem is different. Nevertheless, the main idea of this part is to dismiss sparse data points that can compromise the reliability of the grid.

On the other hand, the second outlier detection, which is the uncertainty delimitation, is defined during the benchmark creation and used during the online evaluation. Such technique is critical for the robustness of the methodology. First of all, the uncertainty evaluation taking advantage of the created thresholds is much faster than the initial outlier detection, a critical factor in the online assessment. In addition, even though the benchmark grid is reliable as aforementioned, the new samples can be different due to malfunctions, novel operation conditions or abnormal behaviours of the system and hence, such labelling indicate to the users that the assessment is not trustworthy. Again, there are not strict rules in order to select the uncertainty thresholds, the distribution of the data and the physical meaning preservation should be the guide to select such delimitations.

***An assessment capable to create new performance scenarios within each operation condition.***

Employing the proliferation strategy in each discretized area of the grid, the assessment can contemplate a broader casuistry of situations, which can indirectly increase the robustness of the evaluation under new performances not previously seen in the database. Such technique consists in performing combinations within different samples to obtain new operation configurations. This artificially created samples can overcome the historical seen performances, providing a more accurate performance assessment.

It should be noticed that one of the main problems of the proliferation, despite the aforementioned discretization issue, is the computational burden associated to its application that could be a drawback even for the benchmark generation. However, if the correct assumptions are made in relation with an industrial refrigeration system, it is possible to simplify the procedure by only performing the proliferation to the samples that can achieve better performances. In this regard, to perform such combinations, only the best historical COP samples of each compressor are considered. This assumption simplifies the application of proliferation techniques and reduce the computational cost of such approaches.

***Conclusions of experimental validation.***

To conclude this assessment methodology, it is validated with the case study, comparing the proposed assessment with the same assessment without considering the affecting variables, identifying abnormal behaviours with the uncertainty labelling and comparing the best historical performances with and without the proliferation technique. The results show that the proposed methodology is able to identify the improvement capabilities considering the current system operation and its degree of uncertainty. This proposed methodology to assess the performance of a refrigeration system is a powerful tool for the operators. It measures the system improvement capabilities, allow the operators to test different control configurations assessing its performances in an objective way and can be used as a basis for fault detection, since constant deviations from its common operation may indicate machine failures.

***Operation improvement***

The path towards the data-driven energy management applied to refrigeration has been continued with the aim to improve the system operation, which was the second aspect to consider. As mentioned in the above conclusions, the methodology is able to detect the compressors improvement capability, hence, the next step is to develop a methodology to recommend near-optimal set points to improve the efficiency of such machinery. This methodology should consider the variables that affect the system performance to provide safe and fast recommendations, needs to preserve the system constraints and should minimize harmful and inefficient set points. Various contributions about this topic are listed and discussed below.

A fast PLR set point recommendation based on historical data and considering the system operation conditions.

This PLR recommendation is grounded on the assessment methodology to create a grid of different operation conditions to recommend robust set points. Furthermore, the proliferation is also employed in each discretized area of the grid to overcome the limitations of the historical data configurations. However, in this scenario, each discretized area should contain the near-optimal PLR of each compressor instead of the performance benchmark. In some neurons, and due to the lack of data in all possible cooling capacities, these PLR curves can present abrupt changes. Hence, since the final goal of the methodology is to recommend PLR set points to the compressors, such curves were processed in order to smooth these abrupt changes that can damage the machinery. The methodologies that interact with industrial systems modifying its operation should grant a safe operation. This fact is especially important in data-driven strategies where the lack of data can compromise this safety.

For the aforementioned reason, even though the PLR curves of the generated grid are processed, the methodology in the set point recommender stage employs different strategies to ensure its safety. First of all, the discretization allows the methodology to achieve a trustworthy PLR curves based on historical samples, and also, allows the proliferation technique. However, the transitions among different neurons can provoke undesired significant changes in the recommended set points. In this regard, a weighted neighbourhood function is employed to smooth these transitions achieving a continuous response of the compressors and avoiding such harmful changes.

***A PLR recommendation that considers the consumption trend and preserves the system constraints.***

On the one hand, the recommendations should ensure the stability in regard to the refrigerant temperature. This property is critical to refrigerate and preserve the product in optimal conditions. Currently, the industrial system employs a PID to control such temperature with a specific strategy to manage the compressors. In the methodology, such particularity is tackled proposing a strategy to modulate the supplied cooling capacity in order to maintain the desired refrigerant temperature. The proposed solution provides an equivalent refrigerant temperature control in regard to the classical PID, however, is able to manage the compressors PLR in a more efficient manner while maintaining the product in the desired conditions as well.

On the other hand, one of the worst scenarios in terms of energy efficiency and compressors safety are the switching actions, which are the starts and stops of these machines. In this regard, one of the focus of this PLR management methodology has been to estimate the evolution of the cooling capacity trend to add robustness to the switching decisions. The current switching strategy do not contemplate future trends and it is prone to make unnecessary switchings. Therefore, the proposed methodology is able to consider future trends and act in consequence. The inclusion of such method has led to achieve greater performances since the number of unnecessary switchings has been drastically reduced.

***Conclusions of the experimental validation.***

The implementation of the methodology in the refrigeration system validates the effectiveness of the proposed methodology and the capability of increasing the compressors efficiency managing the PLR set points. Various scenarios are contemplated with successful results in each one. However, despite obtaining satisfactory result, it is appreciated a gap between the theoretical results versus the experimental ones due to the current control limitations in order to follow the desired set points. In addition, the wear of the machinery is not contemplated by the methodology, factor that can affect the set point recommendation in terms of robustness. Nevertheless, such factor can be mitigated with the previously explained performance assessment methodology, giving an insight of the machinery condition.

### *Load management*

Finally, the last contribution in this data-driven energy management journey has been to improve the refrigeration system acting on the load side, which can be considered as the evaporators management. The cooling load input to each space to refrigerate or the weather conditions cannot be controlled, however, the way to refrigerate such load can be managed with the evaporators. In order to develop a demand side management strategy is fundamental to identify the consumption of each appliance or load. Hence, such identification should be able to obtain these individual values taking advantage of the system acquired variables without adding extra instrumentation. With the individual consumption, and with the random behaviours of the different loads to refrigerate, a real-time management has been proposed without any future estimation that can compromise the product quality. These aforementioned issues, require more attention in literature, especially for the cooling loads. Therefore, innovative methodologies for managing the cooling loads of the refrigeration process conform part of the contributions of this thesis.

***A novel disaggregation technique for cooling loads that only use the monitored variables.***

In literature exist large amount of works addressing this problem, however, none of them approach the problem with the refrigeration particularities. Therefore, the proposed methodology to disaggregate the total consumption applied to cooling loads consists in a novel neural network structure with various layers, each one with its specific function, that only uses the acquired data from the system to identify the individual consumptions.

This novel structure is able to identify such individual consumptions thanks to the capacity to modulate the network weights according to the evaporators status. It is able to be trained with the aggregated data and has the capability to adjust the intermediate layers to each load behaviour. With such novel structure, it is proven that the individual loads can be estimated despite its level of simultaneity.

***A robust and reliable load balancing technique that takes advantage of the disaggregated loads.***

The individual consumption resulting from the disaggregation methodology, is used to balance the load in real-time with an optimization approach. Such approach aims to minimize the peaks and smooth the load shape. This optimization guarantees the product temperature requirements as it is not based on forecasted assumptions. Moreover, it minimizes the operation with two machines in parallel, which highly reduces the efficiency, and improve the COP of the compressors when operating alone. Such approach is selected due to the difficulties predicting the cooling load without introducing huge forecasting errors. In addition, the forecasting would be necessary for each space to refrigerate, and most of such spaces have a random behaviour due to the intrinsic processes developed in them. In a scenario where the cooling loads are known and scheduled, can arise the possibility to integrate forecasting approaches to the methodology in order to improve its effectiveness.

Furthermore, the objective function is selected in regard to the system behaviour and assuming that the demanded load is not modifiable. With the previous methodologies it is possible to guarantee that the generation side of the system is operating in near-optimal conditions. Hence, the objective function in this part of the thesis is to balance the load in order to minimize abrupt changes in the consumption signal that could lead to undesired switching situations or system destabilizations. In this scenario, where the future consumption cannot be estimated in a reliable way, other objective functions such minimization can provoke load pickups that can produce worse efficiencies.

***Conclusions of the experimental validation.***

On the one hand, the load disaggregation method is firstly validated using a mathematical simulation of the system with successful results. The methodology is capable to disaggregate accurately each one of the simulated cooling loads. In addition, once validated mathematically, the methodology is tested in the real refrigeration system with limitations when validating the individual consumption due to the lack of instrumentation. However, even though the limitations, the feasible validation in the real conditions also present favourable results.

On the other hand, the load balancing approach is directly tested in the real system, obtaining promising outcomes in regard to the efficiency improvement. The load management maintains the product with the desired temperature while is able to increase the system efficiency. With this results, it is noticeable that the efficiency of this kind of systems can be improved with the management of the load side. The inherent property of the cooling loads to store energy by themselves proportionate a vast amount of possibilities to manage them, and with the proposed disaggregation strategy, more fine grained management strategies can be developed.

### 6.1.1 Global methodology application and discussion

In this section, a brief summary of the challenges that appeared in order to implement them are presented. As aforesaid, this industrial thesis had the objective to improve the efficiency of an industrial refrigeration system by means of data-driven techniques. For such purpose, the thesis tackled the problem dividing it with the three aforementioned and discussed aspects. For applicability considerations and for the difference among the aspects, each one of them has been converted to an individual methodology that can be used totally separated depending on the user necessities and system particularities, guaranteeing the safety and robustness required to be applied in a real industrial environment.

Concerning this applicability and as a particularity of an industrial thesis, all the proposed methodologies were validated with a real refrigeration system. Such implementation has been a challenging task due to the multiple risks and technical complexity that the fact of testing a novel methodology implies.

On the one hand, the machinery involved in this thesis is very expensive and any damage could have important economic consequences. Moreover, an incorrect management could lead to a huge product loss due to the incapacity to preserve its temperature properties. Therefore, the methodologies had to be tested very carefully in order to avoid huge economic losses, either by the machinery or the products. In this regard, before the application in real-time all the methodologies have been tested with historical data, leaving only as unexplored the part of how they would behave in real-time, to minimize the risks.

On the other hand, and as a distributed system, the methodologies should interact with different controllers allocated in different parts of the company and with different characteristics. The data in order to train and create the methodologies was centralized in a common DDBB, however, in order to apply the management recommendations, the developed software should be able to communicate with all the distributed controllers. Such implication involved modifications in the current controllers program and the implantation of safety measures in case of errors such as the loss of communication or the acquisition of non-trustworthy data, that have not been considered scientific contributions.

In conclusion, the research conducted in this thesis not only contributed improving the current state of the art but are also applicable with reliability in a real industrial system. These methodologies can be used as a basis of an energy management framework and their validity have been contrasted with a real refrigeration system.

## 6.2 Future work

The thesis has paved way towards a more efficient energy management framework applied to refrigeration systems. In this regard, the various blocks approached have initiated new research possibilities aligned with the proposed methodologies.

About the performance assessment:

- The uncertainty thresholds employed in such methodology can be used as a starting point to identify malfunctions in the machinery. Hence, in such scenarios, the affectation of other variables can be used to locate the origin and the root cause of the faults.

- As real systems are dynamic and perform changes during the time, the uncertainty thresholds can be employed as a basis to investigate an efficient automatic retraining to maintain the performance assessment benchmark up to date.
- The assessment in this thesis is done in regard to the compressors performance as they are the components that consume more energy. In future scenarios, the methodology can be employed considering also the condensers, which are the second most consuming element of the system.

In regard to the operation set point recommendation:

- In future studies, the stability issue of the proposed methodology can be improved with the load management data. As the load from the evaporators have a small delay before the compressors notice it, due to the nature of the system, the load management output can be helpful for the operation set point recommendation in order to anticipate the compressors PLR and achieve an ever smoother behaviour.
- The methodology can also be improved considering other compressors variables such as oil pressure or temperature. Such variables that can give an insight of the compressors condition, and may help the methodology to provide a more accurate recommendation for such condition before the next scheduled maintenance.
- As with the assessment methodology, the introduction of the condensers data can improve the overall system performance. This statement opens the approach to suggest set points to the condensers as well.
- With the experimental results obtained, most of the gap between the theoretical and the practical outcomes is attributed to lack of capability to follow efficiently the suggested set points. Therefore, easier suggestions to follow by the controller should be investigated or further efforts should be spent into the PLR control to be able to follow the near-optimal PLR.

With the load management subject:

- In the load disaggregation methodology, different artificial intelligence and deep learning algorithms can be tested to reduce even more the disaggregation error. Such techniques can substitute the default MLPs of each sub-net.
- The parametrization of the proposed neural network structure can be also further studied finding a practical method to parametrize such custom and complex NN structures.
- Further research, concerning with the load management, is to divide the different spaces to refrigerate into random processes and scheduled processes. Thus, the

occupancy of scheduled processes can be modelled to improve the smoothing of the load curve, assuring low modelling errors.

As the presented thesis embrace various important topics of energy management applied to refrigeration, several and challenging options arise in order to continue this research. Moreover, further investigation on these topics open the possibility to extrapolate the listed contributions and advantages to other energy systems or similar areas of application.

# 7.

## Thesis results disseminations

This chapter summarizes the scientific contributions, product from the present thesis, in international journals and conferences.

CONTENTS:

# 7 Thesis results dissemination

Specification of the realized dissemination activities and published papers during the thesis development.

## 7.1 Publications: thesis contributions

List of publications directly related to the contributions of this thesis taking into account journal and conference publications.

### 7.1.1 Journal publications

**J. Cirera**, J. A. Carino, D. Zurita, and J. A. Ortega, "Data analytics for performance evaluation under uncertainties applied to an industrial refrigeration plant," IEEE Access, vol. 7, 2019.

**J. Cirera**, J. A. Carino, D. Zurita, and J. A. Ortega, "A Data-Driven-Based Industrial Refrigeration Optimization Method Considering Demand Forecasting," *Processes* 2020, 8, 617.

### 7.1.2 Conference publications

**J. Cirera**, M. Quiles, J. A. Carino, D. Zurita, and J. A. Ortega, "Data-driven operation performance evaluation of multi-chiller system using self-organizing maps," in Proceedings of the IEEE International Conference on Industrial Technology, 2018, vol. 2018–February.

**J. Cirera**, J. A. Carino, D. Zurita, and J. A. Ortega, "Semisupervised refrigeration plant cooling disaggregation by means of deep neural network ensemble," IEEE Int. Symp. Ind. Electron., vol. 2019–June, pp. 1761–1766, 2019.

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# Annexes

This chapter provides details of the real refrigeration system characteristics and the mathematical simulation. Both systems are used in the development of the present thesis in order to validate the proposed methodologies.

CONTENTS:

# A I Industrial refrigeration system

This industrial research thesis is focused in the energy management topic, and more specifically, applied to industrial refrigeration systems. The validations of the proposed methodologies are tested with one of the refrigeration systems of the Corporació Alimentària Guissona. S.A, the company where the thesis is developed.

The selected refrigeration case study is depicted in **Fig A I.i**, and it consists of an overfeed system with multiple machines operating in parallel due to its dimensionality and the power installed.

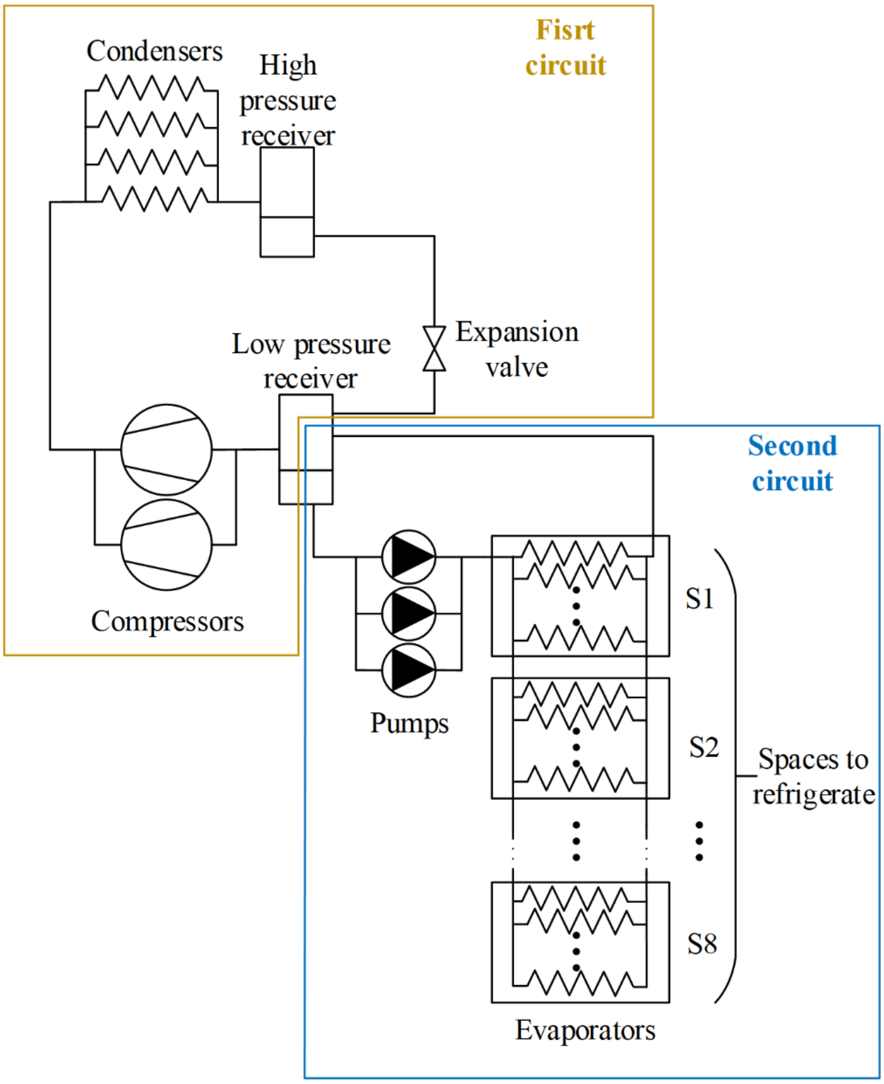



**Fig A I.i –Overfeed refrigeration system scheme of the case study.**

The particularity of this overfeed installations is that they deliver liquid refrigerant, in this case ammonia (R717), to the evaporators at a higher mass flow than it is evaporating. Principally, this system consists of two circuits, the first one is composed by four condensers, two compressors, an expansion device and a low pressure separator receiver. And the second one, which is composed by a low pressure separator receiver, a common element in both circuits, three pumps to force the liquid recirculation and various evaporators distributed in different spaces to refrigerate (S).

In the first circuit, the R717 in vapour state is suctioned by the compressors from the low pressure separator receiver to increase the refrigerant pressure. In order to perform that job, and to provide enough cooling capacity to satisfy the demand, two screw compressors are located in parallel. Subsequently, in the condensers, the refrigerant is cooled to change the phase from vapour to liquid and delivered to the low pressure separator receiver, passing by the expansion valve where the pressure falls down. The condensers block is formed by four evaporative condensers in parallel with five fans and a water pump each one to be able to reject the heat from the refrigerant to the outdoor. Finally, the low-pressure receiver, which is the common part of both circuits, contains R717 in a mixture of vapour-liquid state.

In the second circuit, the refrigerant in liquid state is suctioned by the pumps and led to the evaporators. The pumps are used to guarantee the refrigerant overfeed mass flow through the evaporators distributed alongside the different spaces. Afterwards, in the evaporators located at the different S, the refrigerant is partially evaporated and then returned to the low pressure separator receiver. Besides, each S can contain various evaporators to exchange the heat from the air to the refrigerant.

**Table A I.i** lists the main manufacturer characteristics of the equipment in the first circuit. It should be noticed that such refrigeration systems are highly influenced by the operation conditions, specifically two essential parameters that need to be defined in order to design the installation and calculate the performance and efficiency. These parameters are the suction pressure and the discharge pressure, which in this system are commonly fixed at 1.6bar and 8bar respectively. However, due to high outdoor temperatures and the different processes in the spaces to refrigerate, these set points may change.

**Table A I.i - Main characteristics of the first circuit components.**

| Id | Description | Electrical Power(kW) | Cooling capacity(kW) | COP | Volume(l) |
|---|---|---|---|---|---|
| **C1** | Screw compressor 1 | 450 | 1570 | 3.48 | n/a |
| **C2** | Screw compressor 2 | 450 | 1570 | 3.48 | n/a |
| **Cnd1** | Evaporative condenser 1 | 27 | 3169 | 117.37 | n/a |
| **Cnd2** | Evaporative condenser 2 | 27 | 3169 | 117.37 | n/a |
| **Cnd3** | Evaporative condenser 3 | 27 | 3169 | 117.37 | n/a |
| **Cnd4** | Evaporative condenser 4 | 27 | 3169 | 117.37 | n/a |
| **HPR** | High pressure receiver | n/a | n/a | n/a | 5240 |
| **LPR** | Low pressure receiver | n/a | n/a | n/a | 14780 |

Regarding the second circuit, the **Table A I.ii** shows the main components characteristics. As it can be seen in the table, each S has a different temperature set point and these set points change depending on the production. Such changes affect the suction pressure set point as mentioned, making the system even more dynamic. Data from the evaporators is not available in most cases due to aging of the system and lack of documentation. However, even though such information could be obtained, it is extremely difficult to obtain a trustworthy cooling capacity since factors such as the pipes frosting, the air temperature or the mass flow are difficult to measure and affect the $Q$ value.

**Table A I.ii - Main characteristics of the second circuit components.**

| Id | Description | Nº Evaporators | Tº set point(ºC) | Electrical power(kW) |
|---|---|---|---|---|
| **S1** | Space to refrigerate 1 | 3 | -0.5 | n/a |
| **S2** | Space to refrigerate 2 | 3 | -0.5 | n/a |
| **S3** | Space to refrigerate 3 | 5 | -2/-10 | ≈68 |
| **S4** | Space to refrigerate 4 | 4 | 0 | n/a |
| **S5** | Space to refrigerate 5 | 4 | 0 | n/a |
| **S6** | Space to refrigerate 6 | 4 | -2/1 | n/a |
| **S7** | Space to refrigerate 7 | 6 | -0.8 | ≈72 |
| **S8** | Space to refrigerate 8 | 1 | -0.3 | n/a |
| **P1** | R717 pump 1 | n/a | n/a | 4 |
| **P2** | R717 pump 2 | n/a | n/a | 4 |
| **P3** | R717 pump 3 | n/a | n/a | 4 |

In the refrigeration system and the components that compose it, various signals are acquired in order to monitor and control its operation. To develop the thesis research based on data-driven methodologies, this instrumentation already present in the system is used. Such information is stored in a DDBB every minute and is also used for monitoring purposes in the SCADA. A summary of the principal variables is listed below in **Table A I**.iii.

**Table A I.iii - Summary of refrigeration system main variables.**

| Id | Units | Description |
|---|---|---|
| **dp** | bar | Discharge pressure |
| **sp** | bar | Suction pressure |
| **$PLR_i$** | % | Partial load ratio of compressor *i* |
| **$T_{out}$** | ºC | Outdoor temperature |
| **$Q_C$** | kW | Cooling capacity of the compressor *C* |
| **$P_C$** | kW | Electrical power of the compressor *C* |
| **$P_{Cnd}$** | kW | Electrical power of the condensers |
| **$TSP_S$** | ºC | Set point temperature of the space to refrigerate *S* |
| **$T_S$** | ºC | Indoor temperature of the space to refrigerate *S* |
| **$E_{ON}$** | binary | Evaporator state (ON/OFF) |
| **$E_D$** | binary | Evaporator defrost state (ON/OFF) |

All the aforementioned signals are used by the current control to manage its proper operation. The components of the generation side, which can be considered as the first circuit of the overfeed system, are controlled by a common PLC. Such PLC is in charge to maintain the suction and discharge pressures within the desired set point, controlling, principally, the condensers and the compressors. For the Chapter 3 and Chapter 4 of this thesis, where the objective is to attain a reliable performance evaluation and an efficient set point recommendation of the compressors, the developed software is periodically communicating with this PLC. The training phase is nurtured with the historical DDBB signals but the online software, which is developed in Python, is reading and writing within a certain periodicity the values of the necessary components to measure the compressor efficiency and to recommend the near-optimal PLR set points.

On the other hand, for the demand side, which can be considered as the second circuit which embraces all the spaces to refrigerate distributed within the company facilities, an individual PLC is allocated in each S. Such distribution complicates the Chapter 5 methodology, since the developed software is constantly communicating with the compressors PLC, to acquire the cooling capacity, and also with all the distributed PLCs, to know the temperature of each S and the evaporators state. Therefore, such communication is used to disaggregate the consumption and to suggest a specific number of evaporators turned ON for each S. In regard to the training stage, the DDBB data is used as in the previous methodologies.

In addition, some images of the refrigeration system are provided to depict the main components of the system. In **Fig A I.ii** appears a detail of the compressors allocated in the machine room, a detail of the evaporative condensers allocated at the roof of the facilities in order to remove the heat, and a detail of an evaporator, allocated inside a space to refrigerate in order to refrigerate the products.

a)

b)

c)

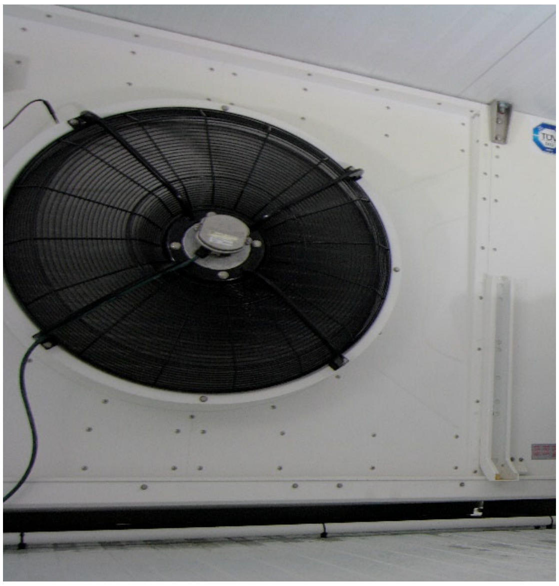


**Fig A I.ii - Photos of the refrigeration system. a) Compressors detail. b) Evaporative condensers detail. e) Evaporator detail.**

**NOTE:** As most of the experimental results are tested in this real refrigeration system, the dataset of such system is uploaded and publicly available in the IEEE DataPort platform [1]. Therefore, all the results are reproducible by the scientific community.

## A I.i References of Annex I

[1] Josep Cirera Balcells, "Industrial overfeed refrigeration system", IEEE Dataport, 2020. [Online]. Available: http://dx.doi.org/10.21227/pyaw-f753.

# A II Mathematical simulation of the refrigeration system

## System

The mathematical simulation is employed to validate the disaggregation methodology since it is non-viable to validate it in the real refrigeration system due to the elevated economic cost that it implies in regard to the necessary instrumentation. This simulation is developed along with the Eurecat Manresa which is a member involved in the MoFriCon project. Such simulation focuses its efforts to the evaporators without pretending to mimic the whole real refrigeration system configuration. Therefore, the simulated system only has one compressor and one condenser unlike the real system where various compressors and condensers operate in parallel. As shown in **Fig A II.i**, in the evaporators side, 8 spaces to refrigerate are allocated in parallel with one evaporator in each space. Thus, the presented configuration is suitable to validate the disaggregation methodology.

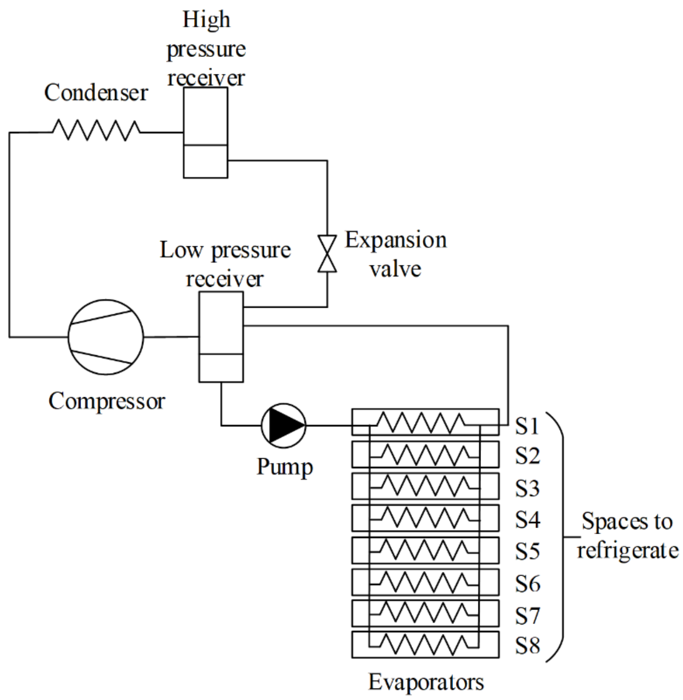



**Fig A II.i - Overfeed scheme of the mathematical simulation.**

## Assumptions

To simulate the system, various mathematical equations that emulate the real behaviour of the different components are used. Nevertheless, since the purpose of the simulation is to validate the data-driven methodologies, some assumptions are made to reduce the complexity of the refrigeration cycle:

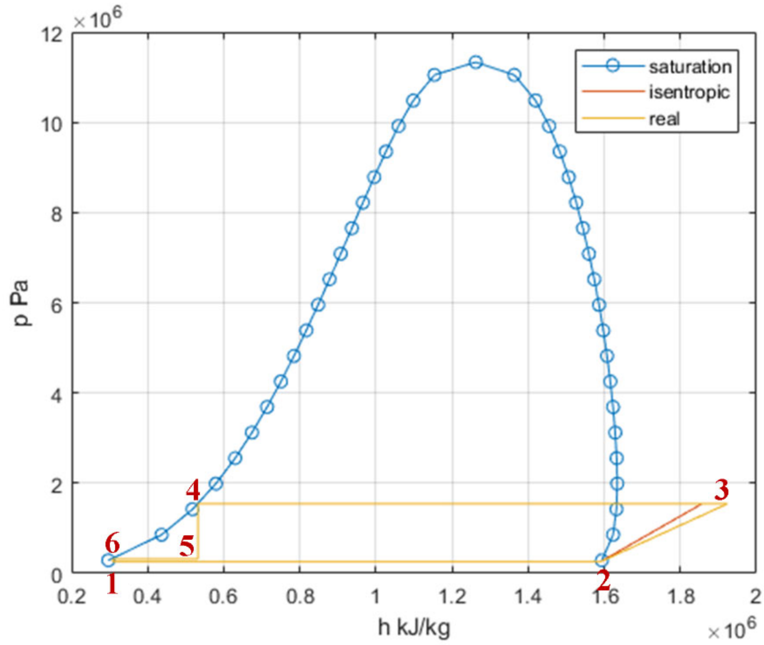
- The cycle is calculated in steady state, having to iterate the simulation various steps to mimic the behaviour over the time.
- It is assumed that there are not thermal or pressure losses in the connections between the components of the system.
- It is considered that the pressure and the temperature is homogeneous in each component.
- Pressure losses inside the evaporator and the condenser are not considered.
- The accumulation of energy in the exchangers is not considered.
- The evaporation temperature is fixed.
- The refrigerant at the outlet of the evaporators should be in saturated conditions in order to calculate the fluid mix.
- The employed refrigerant is ammonia (R717).
- Each space to refrigerate act as two heat exchangers between:
    - The evaporator and the cooling load.
    - The thermal load and the outdoor to simulate the cooling losses.
- The temperature in each cycle remains constant till the next iteration.

- In order to differentiate the evaporators power characteristics in terms of cooling capacity, the UA parameter is modified.

## Diagrams

Previous to the presentation of the system equations, the refrigeration cycle is depicted in **Fig A II.ii** with a pressure-enthalpy and temperature-entropy diagrams in order to identify the behaviour of an overfeed system, and label the different steps of the cycle.

a)




b)

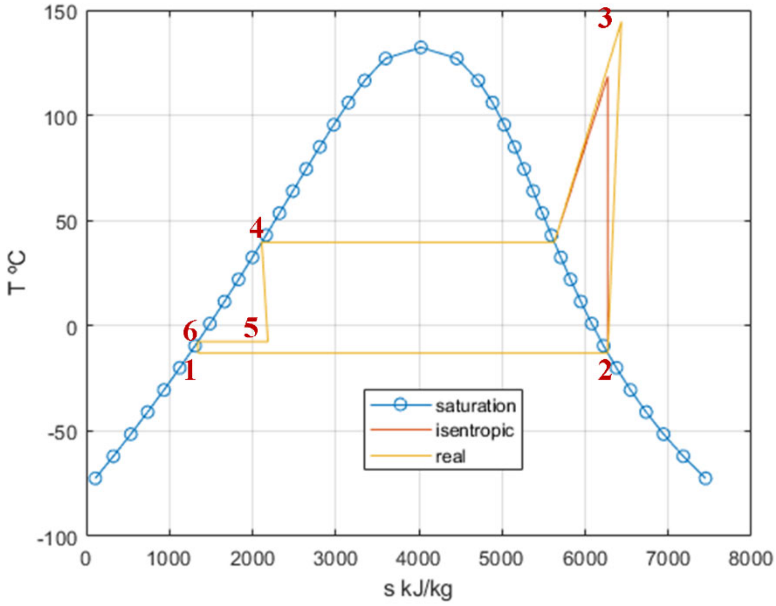



**Fig A II.ii – Diagrams of the overfeed refrigeration system. a) Pressure-enthalpy. b) Temperature-entropy.**

## Nomenclature

Another information that should be provided previous to the equations is the nomenclature, **Table A II.i**.

**Table A II.i - Nomenclature employed in this mathematical simulation.**

| Id | Units | Description |
|---|---|---|
| $h_1$ | J/kg | Evaporator inlet enthalpy |
| $h_2$ | J/kg | Compressor inlet enthalpy |
| $h_3$ | J/kg | Compressor outlet enthalpy |
| $h_4$ | J/kg | Condenser outlet enthalpy |
| $h_5$ | J/kg | Intermediate expansion enthalpy |
| $h_6$ | J/kg | Low pressure receiver enthalpy |
| $s_1$ | J/kg·K | Evaporator inlet entropy |
| $s_2$ | J/kg·K | Compressor inlet entropy |
| $s_3$ | J/kg·K | Compressor outlet entropy |
| $s_4$ | J/kg·K | Condenser outlet entropy |
| $s_5$ | J/kg·K | Intermediate expansion entropy |
| $s_6$ | J/kg·K | Low pressure receiver entropy |
| $T_1$ | K | Evaporator inlet temperature |
| $T_2$ | K | Compressor inlet temperature |
| $T_3$ | K | Compressor outlet temperature |
| $T_4$ | K | Condenser outlet temperature |
| $T_5$ | K | Intermediate expansion temperature |
| $T_6$ | K | Low pressure receiver temperature |
| $P_s$ | Pa | Suction pressure |
| $P_d$ | Pa | Discharge pressure |
| P5 | Pa | Intermediate expansion pressure |
| $\Pi$ | n/a | Compression ratio |
| $\dot{Q}_{evap}$ | W | Heat absorbed by the evaporator |
| $\dot{Q}_{cond}$ | W | Heat rejected by the condenser |
| $W_s$ | W | Isentropic compressor electrical power |
| $W_{comp}$ | W | Compressor electrical power considering isentropic performance |
| $W_{el}$ | W | Compressor electrical power considering electromechanical performance |
| valve | % | Compressor slide valve |
| $\eta_v$ | n/a | Compressor volumetric performance |
| $\eta_s$ | n/a | Compressor isentropic performance |
| $\eta_{el-me}^{nominal}$ | n/a | Compressor nominal electromechanical performance |
| $\eta_{el-me}$ | n/a | Compressor electromechanical performance |
| $T_{evap}$ | ºC | Evaporation temperature |
| $T_i$ | ºC | Initial load *i* temperature of current timestep |
| $T_i^{new}$ | ºC | Final load *i* temperature of current timestep |
| $Cp_i$ | J/kg·K | Specific heat of load *i* |
| $\dot{m}$ | kg/s | Mass flow rate |
| $\dot{m}_{comp}^{max}$ | kg/s | Maximum mass flow rate of the compressor |
| $\dot{m}_{comp}^{min}$ | kg/s | Minimum mass flow rate of the compressor |
| $\Delta t$ | s | Timestep duration |
| $Q_i$ | W | Cooling load *i* |
| $Q_{loss\ i}$ | W | Cooling load *i* losses |
| $UA_i$ | W/K | Evaporator *i* heat transfer coefficient |
| $UA_{loss,i}$ | W/K | Cooling load *i* losses heat transfer coefficient |
| $T_{loss,i}$ | ºC | Cold loss focus temperature |
| $mass_i$ | kg | Load *i* mass |
| $TSP_i$ | ºC | Load *i* temperature set point |
| $\chi$ | % | Vapour quality (100=saturated vapour; 0=saturated liquid) |
| $TSP_{db,i}$ | ºC | Load *i* deadband of the temperature set point |

## Equations

With the diagrams illustrated and the nomenclature of the subsequent equations listed, the equations extracted from J. Winkler [1], M. Bilgili [2], M. Shapiro [3] and A. Sadurní [4] detailed below are employed to simulate the system:

Starting point

Considering a fixed evaporation temperature T1=T2 and under saturated vapour conditions of the refrigerant.

$$h_2 = f(T_2, \chi = 100)$$ **Eq. A II.i**

Compressor

Considering a fixed discharge pressure and ideal isentropic properties.

$$s_2 = s_3$$ **Eq. A II.ii**

$$h_{3s} = f(P_d, s_3)$$ **Eq. A II.iii**

$$\dot{W}_s = \dot{m}\,(h_{3s} - h_2)$$ **Eq. A II.iv**

Considering a real compressor.

$$\dot{W}_{comp} = \frac{\dot{W}_s}{\eta_s}$$ **Eq. A II.v**

$$h_3 = \frac{(h_{3s} - h_2)}{\eta_s} + h_2$$ **Eq. A II.vi**

$$\eta_{el-me} = f(valve_2, \eta_{el-me}^{nominal})$$ **Eq. A II.vii**

$$\dot{W}_{el} = \frac{\dot{W}_{comp}}{\eta_{el-me}}$$ **Eq. A II.viii**

Condenser

$$h_4 = f(Pd, \chi = 0)$$ **Eq. A II.ix**

$$\dot{Q}_{cond} = \dot{m}\,(h_3 - h_4)$$ **Eq. A II.x**

Expansion valve

$$h_5 = h_4$$ **Eq. A II.xi**

$$P_5 = (P_d - P_s) \cdot 0.05 + P_s$$ **Eq. A II.xii**

$$h_6 = f(P_5, \chi = 0)$$ **Eq. A II.xiii**

$$h_1 = h_6$$ **Eq. A II.xiv**

Evaporator

$$\dot{Q}_{evap} = \dot{m}\,(h_2 - h_1)$$ **Eq. A II.xv**

Mass flow regulation

The mass flow is modulated using the slide valve of the screw compressors.

$$\dot{m} \;= valve \cdot \left(\dot{m}_{comp}^{max} - \dot{m}_{comp}^{min}\right) \cdot \eta_v$$ **Eq. A II.xvi**

COP and compression ratio

$$COP = \frac{\dot{Q}_{evap}}{\dot{W}_{el}}$$ **Eq. A II.xvii**

$$\Pi \;= \frac{P_d}{P_s}$$ **Eq. A II.xviii**

Cooling load

$$\frac{d}{dt}(m_i Cp_i T_i) = \dot{Q}_i - \dot{Q}_{loss\ i}$$ **Eq. A II.xix**

$$m_i \cdot Cp_i \cdot \frac{T_i - T_i^{new}}{\Delta t} = Q_i - Q_{loss\ i}$$ **Eq. A II.xx**

$$T_i^{new} = T_i - \frac{Q_i - Q_{loss\ i}}{mass_i Cp_i} \cdot \Delta t$$ **Eq. A II.xxi**

$$Q_i = UA_i \cdot \left(T_i - T_{evap}\right)$$ **Eq. A II.xxii**

$$Q_{loss\ i} = UA_{loss,i}(T_i - T_{loss,i})$$ **Eq. A II.xxiii**

$$\sum Q_i \leq Q_{evap}$$ **Eq. A II.xxiv**

In order to simulate the system, some values should be fixed to certain operation conditions as shown in **Table A II.ii**. Additionally, the thermodynamic properties of the employed refrigerant, the R717, are calculated using the CoolProp library. Note that some of them are put into brackets to enumerate each value of each space to refrigerate.

**Table A II.ii - Value of the necessary variables to perform the refrigeration cycle simulation.**

| Variable | Value |
|---|---|
| $T_{evap}$ | -13 |
| $\Pi$ | 6 |
| $\eta_s$ | 0.8 |
| $\eta_v$ | 0.8 |
| $\eta_{el-me}^{nominal}$ | 0.9 |
| $\dot{m}_{comp}^{max}$ | 706 |
| $\dot{m}_{comp}^{min}$ | 1694 |
| valve | 100 |
| $mass_i$ | [1;0.5;0.25;0.8;0.9;0.2;0.6;0.3] |
| $Cp_i$ | [4000;4000;4000;4000;4000;4000;4000;4000] |
| $T_i$ | [7;2;4;5;-1;3;4;6] |
| $UA_i$ | [1;1.5;2.0;1.2;1.3;2.2;0.8;1.9] |
| $TSP$ | [-8;-10;-6;-9;-5;-2;-10;-7] |
| $TSP_{db,i}$ | [2,2,2,2,2,2,2,2] |
| $T_{loss,i}$ | [1,1,1,1,1,1,1,1] |
| $UA_{loss,i}$ | [0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1] |
| $\Delta t$ | 1 |

**Simulation**

The simulation has been performed, approximately, for a period of time of 8500 seconds. Each space to refrigerate, has one load and one evaporator, with the same type of load but with different masses, temperature set points and evaporators power in all the spaces. These initial values of the simulation are depicted in **Table A II.ii**.

Nevertheless, the values of the masses inside each space are changed randomly between 1 and -1 each time that the load reaches the temperature set point. With these changes, the simulation pretends to emulate the real behaviour of the processes that are done inside each space, where various products are constantly input and output. It should be noticed that the magnitude of the values does not try to mimic the real industrial refrigeration system, the purpose of the simulation is only to validate the disaggregation methodology.

## A II.i References of Annex II

[1] Jonathan Winkler, Vikrant Aute, Reinhard Radermacher. Comprehensive investigation of numerical methods in simulating a steady-state vapour compression system. International Journal of Refrigeration (2008) 930–942. DOI: 10.1016/j.ijrefrig.2007.08.008

[2] Mehmet Bilgili. Hourly simulation and performance of solar electric-vapour compression refrigeration system. Solar Energy 85 (2011), pp 2720-2731. DOI: 0.1016/j.solener.2011.08.013

[3] Moran, M.J., Shapiro, H.N., 2006. Fundamentals of Engineering Thermodynamics, fifth ed. John Wiley and Sons Inc, England, ISBN: 978-0-470-03037-0.

[4] Sadurni, A. [et al.]. Analysis of vapour-compression refrigerating systems. A: IIR International Congress of Refrigeration. "Proceedings of 23rd IIR International Congress of Refrigeration". 2011, p. 1-8.