UNIVERSIDAD DE CHILE
FACULTAD DE CIENCIAS FÍSICAS Y MATEMÁTICAS
DEPARTAMENTO DE INGENIERÍA ELÉCTRICA

IMPACT OF NON-COMPLIANCE IN CONSUMPTION SCHEDULES OF SMART DISTRIBUTION NETWORKS WITH PRICE-BASED DEMAND RESPONSE PROGRAMS

TESIS PARA OPTAR AL GRADO DE MAGÍSTER EN CIENCIAS DE LA INGENIERÍA, MENCIÓN ELÉCTRICA

MEMORIA PARA OPTAR AL TÍTULO DE INGENIERO CIVIL ELÉCTRICO

DANIEL OMAR ESCOBAR SCHNEIDER

PROFESOR GUÍA:
PATRICIO MENDOZA ARAYA

PROFESOR CO-GUÍA:
RODRIGO PALMA BEHNKE

MIEMBROS DE LA COMISIÓN:
SANDRA CÉSPEDES UMAÑA
LORENZO REYES CHAMORRO

SANTIAGO DE CHILE
2022

RESUMEN DE LA TESIS PARA OPTAR
AL GRADO DE MAGÍSTER EN CIENCIAS
DE LA INGENIERÍA, MENCIÓN ELÉCTRICA
POR: **DANIEL OMAR ESCOBAR SCHNEIDER**
FECHA: 2022
PROF. GUÍA: PATRICIO MENDOZA ARAYA

IMPACTO DEL INCUMPLIMIENTO EN LA PROGRAMACIÓN DEL CONSUMO DE REDES DE DISTRIBUCIÓN INTELIGENTES CON PROGRAMAS DE RESPUESTA A LA DEMANDA BASADOS EN EL PRECIO

La gestión de demanda residencial entrega beneficios a las redes eléctricas, que reducen los costos de operación. Sin embargo, la efectividad de la gestión de demanda residencial puede depender del comportamiento humano, viéndose afectada si este no es el esperado.

En este trabajo se estudia el impacto del incumplimiento en la gestión de demanda de usuarios residenciales. Se crean usuarios ficticios con preferencias para sus dispositivos y bienestar. Luego, se definen los incumplimientos y se opera el sistema simulado. A partir de los diferentes escenarios se analizan los costos de operación para diferentes cantidades de usuarios en incumplimiento y magnitudes del desvío.

Los resultados muestran que para desvíos pequeños de consumo el sistema tolera altos porcentajes de incumplimiento, alcanzando sobrecostos cercanos al 1 %. Cuando el desvío es mayor no se garantiza la conveniencia de la gestión de demanda, alcanzándose sobrecostos cercanos al 5 %, volviendo inconveniente la gestión de demanda. Se concluye que un agregador de demanda puede permitir cierto nivel de desvío en todos sus usuarios sin verse afectado, siendo para el caso de estudio un 25 % de desvío de su valor de ω_2.

RESUMEN DE LA TESIS PARA OPTAR
AL GRADO DE MAGÍSTER EN CIENCIAS
DE LA INGENIERÍA, MENCIÓN ELÉCTRICA
POR: **DANIEL OMAR ESCOBAR SCHNEIDER**
FECHA: 2022
PROF. GUÍA: PATRICIO MENDOZA ARAYA

IMPACT OF NON-COMPLIANCE IN CONSUMPTION SCHEDULES OF SMART DISTRIBUTION NETWORKS WITH PRICE-BASED DEMAND RESPONSE PROGRAMS

Residential demand management provides benefits to electric grids that reduce operating costs. However, the effectiveness of residential demand management may depend on human behavior, being affected if it is not as expected.

In this work we study the impact of non-compliance in the demand management of residential users. Fictitious users with preferences for their devices and welfare are created. Then, non-compliances are defined and the simulated system is operated. Based on the different scenarios, the operating costs for different amounts of non-compliance users and diversion magnitudes are analyzed.

The results show that for small consumption deviations, the system tolerates high non-compliance percentages, reaching cost overruns close to 1 %. When the deviation is higher, the convenience of demand management is not guaranteed, reaching cost overruns close to 5 %, making demand management inconvenient. It is concluded that a demand aggregator can allow a certain level of deviation in all its users without being affected, being for the case of study a 25 % deviation from its ω_2 value.

A mi hermana Belén
y a mis padres Daniel y Claudia.

Agradecimientos

A mi familia, por el apoyo incondicional que me han brindado en esta etapa, por sus enseñanzas y formación como estudiante y sobretodo como persona. Gracias a ustedes he llegado hasta donde estoy ahora. No saben cuánto agradezco el cariño, las risas y los buenos momentos que me entregan y que me dan energía para seguir adelante.

A Valentina, que me ha acompañado y alentado cuando más lo he necesitado. Tu amor, cariño, y comprensión han sido muy importantes para sobreponerme a los momentos más difíciles. Te agradezco de corazón por siempre estar ahí y darme ánimo para no rendirme. Gracias por los lindos momentos que hemos vivido y los que vendrán.

También agradezco a mis amigos y amigas que me han acompañado en todo este proceso. Guardo con mucho cariño todos las experiencias y momentos que compartimos a lo largo de estos años, y sé que vendrán muchos más. Les agradezco de corazón sus consejos y compañía, gracias por ser parte de mi vida y por permitirme ser parte de la ustedes.

A mi profesor guía Patricio Mendoza, por las enseñanzas que me ha entregado y por darme la oportunidad de trabajar con él. Le agradezco por darse el tiempo de reunirse conmigo todas las semanas y siempre aportar con comentarios constructivos. Gracias por su buena voluntad y disposición para ayudarme a avanzar en el trabajo que construimos.

Table of Content

Table index

Index of Illustrations

Nomenclature

ϵ_i coefficient that indicates the importance given by the user to the appliance i

η, γ Coefficients representing the thermal conditions of the environment.

η^c_{ESS} Charge efficiency of the storage system.

η^d_{ESS} Discharge efficiency of the storage system.

λ Constant for unit conversion.

λ_{buy} Electricity purchase price $[\frac{Cents}{kWh}]$.

λ_{sell} Electricity selling price $[\frac{Cents}{kWh}]$.

$\mathcal{A}$ Set of user appliances, $\mathcal{A} = \mathcal{A}_{in} \cup \mathcal{A}_{non} \cup \mathcal{A}_{ther} \cup \mathcal{A}_{unman}$

$\mathcal{A}_{in}$ Set of non interruptible appliances.

$\mathcal{A}_{non}$ Set of interruptible appliances.

$\mathcal{A}_{non}$ Set of unmanageable appliances.

$\mathcal{A}_{ther}$ Set of thermostatically controlled appliances.

$\mathcal{B}$ Set of busbars.

$\mathcal{L}$ Set of transmission lines.

$\mathcal{T}$ Set of time periods.

μ_{ESS} Binary variable indicating the charge (1) or discharge (0) of the battery.

ω_1 Weight of cost minimization.

ω_2 Weight of dissatisfaction minimization.

ω'_2 Value of ω_2 given a deviation in demand management compliance.

ρ_{wh} Hot water demand [kg].

θ^{dn}_i Minimum desired temperature for the appliance i.

θ^{up}_i Maximum desired temperature for the appliance i.

$\theta_{from(l)}$ Function indicating the angle of the bar of origin of f_l.

$\theta_{from(l)}$ Function indicating the angle of the destination busbar of f_l.

ζ_i User dissatisfaction caused by the appliance i.

AC Set of Air Conditioning appliances.

$bus(g)$ Function that indicates the busbar to which the generator g is connected.

c_w Specific heat of water [J/kg/°C].

$C_{emergency}$ Cost function of emergency generation.

C_i Cost function of the generator i.

$D_{b_{expected}}$ Expected demand at busbar b.

$D_{b_{real}}$ Real demand at busbar b.

E_i^{APP} Energy required by appliance i during a period [kWh].

f_l Flow through line l.

$f_{max}(l)$ l line capacity.

$from(l)$ Function indicating the originating busbar of the flow f_l.

J_1 User operation cost.

J_2 User dissatisfaction level.

L_i Time at which the appliance i is allowed to start operating.

M Mass of water in full storage [kg].

m Mass of water demand in a period [kg].

ng Number of generators.

nl Number of busbars.

nl Number of lines.

P_i^{APP} power consumed by the appliance i [kW].

P_{buy} Power purchased from the grid [kW].

P_{ESS}^c Charging power of the storage system.

P_{ESS}^d Discharging power of the storage system.

P_{ESS}^{sold} Power sold by the storage system [kW].

P_{ESS}^{use} Power used by the storage system [kW].

$P_{i_{max}}$ Maximum power of generator i.

$P_{i_{min}}$ Minimum power of generator i.

P_i Power generated by the unit i.

P_{loss_b} Power that cannot be supplied at bus b.

$P_{non-mana}$ Unmanageable power.

P_{PV} Total power obtained from PV system.

P_{PV}^{sell} Power sold from PV system.

P_{PV}^{use} Power used from PV system.

P_{sell} Power sold to the grid [kW].

R_{ESS}^{c} Maximum charging rate of the storage system.

R_{ESS}^{d} Maximum charging rate of the storage system.

S_{ESS} State of energy of the storage system

S_{ESS}^{ini} Initial state of energy of the storage system

S_{ESS}^{max} Maximum state of energy of the storage system

S_{ESS}^{min} Minimum state of energy of the storage system

$T_{c,i}$ More comfortable temperature in the appliance i.

T_{cold} Temperature of inlet cold water[°C].

$T_{L,i}$ Required device power-on duration of the appliance i.

$T_{u,i}$ temperature of the user's appliance i at time [°C].

$to(l)$ Function that indicates the destination busbar of the flow f_l.

U_i Time limit for the operation of the appliance i.

u_i^{APP} binary variable indicating the switching on or off of the appliance i.

u_i Binary variable of turn-on of unit i.

$w_{1,i}$ Weight of being at a lower temperature than the desired by the user i.

$w_{2,i}$ Weight of being at the desired temperature by the user i.

$w_{3,i}$ Weight of being at a higher temperature than the desired by the user i.

WH Set of Water Heater appliances.

$z_{1,i}, z_{2,i}$ Auxiliary variables to limit range of values of $w_{1,i}$, $w_{2,i}$ and $w_{3,i}$.

Chapter 1

Introduction

1.1. Motivation

The Smart Grids are described by the IEEE as the next-generation electrical power system that is typified by the increased use of Communications and Information Technology in the generation, delivery and consumption of electrical energy. The transition to Smart Grids in the energy sector brings new alternatives to the optimization of its operation in technical and economic aspects. One of the new applications in Smart Grids, promoted by the advances in telecommunications such as the Internet of Things (IoT) [1], is the management of demand at industrial and residential level, being the latter the scope of this thesis.

The incorporation of this new application in the grid translates into several system advantages, by giving, in principle, the network operator greater controllability, helping to reduce operating costs; by shifting the load demand to times when energy is cheaper, as it would be in hours with a high amount of renewable generation; or by providing support in contingencies through disconnection of loads previously configured by the user; among other functionalities [2].

Despite the advantages of demand management, its implementation implies new challenges for the operation of the network, such as the knowledge of user behavior [3]. Within the knowledge of user behavior there are challenges such as determining how the users will respond to incentives, and the possibility that they may not behave as expected (which as an aggregate effect of several users may modify the amount of demand managed, affecting the effectiveness of demand management). Linked to these challenges arise questions that motivate the studies carried out in this thesis: How can one determine the responses of a particular user to the price signals provided? What happens if a user commits to a certain demand profile, but deviates from such commitment? To what extent is the system able to withstand this non-compliance? These questions are the main motivation for this study, which seeks to analyze the impact on the system when the user behavior is not as expected.

The impact generated by non-compliance with the consumption schedule depends on the control of the loads (which can be remote, hybrid, or manual) through price signals or other mechanisms, and how satisfied the users are with the management of their loads [4]. This thesis considers a centralized demand management based on price signals, in which users commit a certain consumption profile based on an economic incentive, in which compliance with the schedule depends on the user, such that, despite providing the operator with user behavior information, this could differ from what is expected.

Previous works have focused on the construction of demand management models that minimize user dissatisfaction, allow for greater penetration of renewable energies, or optimize costs through game theory, among others [5] [6]. However, little has been studied about the impact that the system would suffer if the profiles established from the models were not fulfilled. From the state-of-the-art techniques, the proposals with robust economic dispatch models considering demand management are among the most advanced [3], however the impact of non-compliance with the consumption schedule is not addressed in the literature, recognizing here an important research gap.

In view of the upcoming massification of this application, and considering the need to address this research gap, the purpose of this thesis is to study the effects on operating costs of non-compliance with consumption schedules at the residential level with demand management based on price signals. The necessity of having a model to predict the non-compliance of users, and the consideration of non-compliance in the operation of the system are the subjects of this work. Understanding the impacts of non-compliance enables better decision making: if the impact on the operating costs is low, it might not be necessary to implement these models in the system (considering that this implies a cost); however, if the impact is high, non-compliance should be incorporated in detail into the operation principles of Smart Grids.

1.1.1. Enerdis

The study elaborated in this thesis arises from an entrepreneurship that is developed jointly with other Master students of the Electrical Engineering Department, and is currently part of the incubation program of Open Beauchef. This entrepreneurship, called Enerdis, seeks to implement demand management at the residential level with the objective of maximizing the self-generation of users who have solar panels in their residence. In this way, users reduce their electricity bills and reduce their carbon footprint by shifting their consumption so that during the most polluting hours less energy is generated with energy sources such as coal or diesel.

This demand management is sought to be achieved, once the entrepreneurship has matured, through price signals to the user. Once the user has received the price signal, he indicates how his consumption will be during the day. Based on this consumption profile, demand is managed automatically or manually. The manual management gives the possibility that users do not fulfill their daily consumption promise, which can be detrimental to the system.

From the aforementioned application, there is an interest in investigating non-compliance in demand management. In particular, the aim is to determine the maximum level of non-compliance by demand management users that is still convenient for the system. From the project's viewpoint, it is expected that a low level of non-compliance does not jeopardize the demand management.

1.2. Hypothesis Statement

The hypothesis of this thesis is that demand management considering voluntary participation schemes is economically convenient even when considering non-compliance by users.

1.3. Objectives

This section presents the objectives of the thesis work.

1.3.1. General Objective

The main objective of the research is to determine and analyze the impact produced on the operating costs by the non-compliance of the consumption schedule of residential users obtained from the Demand Response Program on an electrical system.

1.3.2. Specific Objectives

In order to meet the general objective, the specific objectives are defined as follows:

1. Identify the main challenges in non-compliance modeling through a state-of-the-art review on Demand Side Management and Demand Response.

2. Implement a model that, given a price signal and user preferences, determines the expected response of a user participating in demand management.

3. Perform a sensitivity analysis of non-compliance in demand management on a simulation testbed system and a set of virtual users considering their preferences and appliances.

4. Determine and analyze the impact on operating costs that non-compliance in demand management may cause on the system.

1.4. Scope

Since this thesis focuses on non-compliance by residential users, the scope is limited to this type of consumption. Hence, no commercial or industrial users are considered in the study.

To analyze the impact on costs, a simple dispatcher was used to complement the operation of the system, so the operating costs may vary if a more detailed dispatcher is utilized; however, the analysis of results and conclusions are not affected. Additionally, the CREST model [7] is used for the creation of users, which was built based on users located in the United Kingdom; if it is desired to study the impact of non-compliance for the particular case of Chile or another country, an adjustment in the model becomes necessary.

According to the used simple dispatcher, similar to those proposed in [8] and [9], the scope of the thesis considers a time horizon of 24 hours, the same horizon of the demand management model. In addition and not less important, this is the horizon with which Enerdis seeks to work, sending daily price signals to which users respond with their consumption promises. For this reason, using a horizon longer than 24 hours would not be consistent with the objectives of Enerdis, since it would be difficult for a user to commit a consumption for longer time horizons, for example, one week.

In addition, considering that the scope is within the Enerdis project, it considers manual demand management by users in order to reduce electricity bills and system operating costs, without considering the impact that these benefits could have for generators. Linked to the above, the study is limited in scope in terms of neglecting reserve markets or complementary services in which demand management can participate.

Chapter 2

Background

This chapter explores the most relevant concepts for the development of this thesis, considering concepts associated to the electric system, such as demand side management and concepts associated to a type of user that participates in demand side management, like the type of loads it owns.

2.1. Smart Grids

The scenario in which the study takes place considers the presence of a smart grid (SG), where the contrast with a traditional power grid is that it has a bidirectional flow of energy and information [10] so that an automated and distributed advanced energy delivery network is created. Table 2.1 shows the main differences between a smart grid and a traditional power grid. As for the exact definition of what a SG is, there is no single definition that is accepted, and is different for each organization. Some of the definitions that are handled for the Smart Grid concept are explicitly quoted below [11]:

- IEEE: The “smart grid” has come to describe a next-generation electrical power system that is typified by the increased use of Communications and Information Technology in the generation, delivery and consumption of electrical energy.
- IET: The Smart Grid is fully functional around 2030 that will cost efficiently integrate the actions of all users connected to it – generators, consumers and those that do both – in order to ensure an economically efficient, sustainable power system with low losses and high levels of quality and security of supply and safety.
- AEMO (Australian Energy Market Operator): Smart Grid creates opportunities for consumers to change their energy consumption at short notice in response to a variety of signals that include price signals.
- IESO (Ontario ISO): Using information and communication technologies (especially smart meters) to expand the capabilities of the electricity system to provide even greater benefits for consumers.
- Climate Group: A “smart grid” is a set of software and hardware tools that enable generators to route power more efficiently, reducing the need for excess capacity and allowing two-way, real time information exchange with their customers for real time

Demand Side Management (DSM). It improves efficiency, energy monitoring and data capture across the power generation and T&D grid.

- ABB: A smart grid is an evolved grid system that manages electricity demand in a Sustainable, Reliable and Economic manner, built on advanced infrastructure and tuned to facilitate the integration of all involved.

- Ofgem: A Smart Grid as part of an electricity power system can intelligently integrate the actions of all users connected to it -generators, consumers and those that do both- in order to efficiently deliver sustainable, economic and secure electricity supplies.

Table 2.1: Comparison between a traditional grid and a smart grid [10]

Traditional Grid	**Smart Grid**
Electromechanical	Digital
One-way communication	Two-way communication
Centralized generation	Distributed generation
Few sensors	Sensors throughout
Manual monitoring	Self-monitoring
Manual restoration	Self-healing
Failures and blackouts	Adaptive and islanding
Limited control	Pervasive control
Few customer choices	Many customer choices

To make possible the change from a traditional grid to a smart grid is necessary to use ICTs, artificial intelligence, cybersecurity technologies, among others, which implies a higher investment cost compared to a traditional electric grid, but with this a clean, safe, secure, reliable, resilient, efficient, and sustainable grid is achieved. This can be achieved thanks to the new uses that the new technologies present in the grid provide, allowing the reduction of peak demand and a greater entry of renewable energies, or increasing the resilience of the system. Linked to the requirements and benefits provided by an SG, [10] proposes the following list where this information is synthesized:

1. Improving power reliability and quality.

2. Optimizing facility utilization and averting construction of back-up (peak load) power plants.

3. Enhancing capacity and efficiency of existing electric power grids.

4. Improving resilience to disruption.

5. Enabling predictive maintenance and self-healing responses to system disturbances.

6. Facilitating expanded deployment of renewable energy sources.

7. Accommodating distributed power sources.

8. Automating maintenance and operation.

9. Reducing greenhouse gas emissions by enabling electric vehicles and new power sources.

10. Reducing oil consumption by reducing the need for inefficient generation during peak usage periods.

11. Presenting opportunities to improve grid security.

12. Enabling transition to plug-in electric vehicles and new energy storage options.

13. Increasing consumer choice.

14. Enabling new products, services, and markets.

The model to fulfill the above mentioned of a SG, has seven domains [10] shown in table 2.2 and three systems responsible for the proper functioning of the grid. These seven domains are the ones that make up the intelligent grid and interact with each other through energy or information flows, being the aforementioned systems the ones in charge of keeping all the domains cohesive.

Table 2.2: Domains in a Smart Grid [10]

Domain	**Actors in the Domain**
Customers	The end users of electricity. May also generate, store, and manage the use of energy.
Markets	The operators and participants in electricity markets.
Service Providers	The organizations providing services to electrical customers and utilities.
Operations	The managers of the movement of electricity.
Bulk Generation	The generators of electricity in bulk quantities. May also store energy for later distribution.
Transmission	The carriers of bulk electricity over long distances. May also store and generate electricity.
Distribution	The distributors of electricity to and from customers. May also store and generate electricity.

The systems that make up a SG are [10]:

- Smart Infrastructure System: Corresponding to the infrastructure for energy, communication and information, is capable of supporting bidirectional flows of information and energy, i.e., the energy flow is not only from generators to consumption. The flow can also be in the opposite direction thanks to distributed generation or storage systems. On the other hand, the bidirectional flow of information indicates that now the consumers, or other final elements of the grid, are able to send information upstream so that the grid operator operates closer to the optimum by having greater control.

  This system is divided into three subsystems:

  - Smart Energy Subsystem: Responsible for transmission, generation and consumption of energy.

- Smart Information Subsystem: Responsible for the measurement, monitoring and control of SG.
- Smart Communication Subsystem: Responsible for the connectivity and transmission of information between the system, devices and applications.

- Smart Management System: Is the system in charge of advanced management and control services and functionalities. This system is the main responsible for the transition to what is known as SG, because for this to happen, the smart infrastructure that conforms it must be exploited, so that new applications and services for the grid emerge.

  To make this possible, the Smart Management System exploits the Smart Infrastructure to meet its management objectives, the aims of which are to improve energy efficiency, balance supply and demand, control emissions, reduce operating costs and maximize utility.

- Smart Protection System: In this system are found the protections against failures and reliabilty analysis, on the other hand, there are also the privacy and information security services. In addition to smarter management, smart infrastructure tools should also be used for better system protection, adding more support in contingencies and including cyber security in the system, considering that a greater amount of information is handled, much of which can be considered sensitive, such as user consumption information, or the routes taken by electric vehicles.

2.2. Electricity Demand

As a counterpart to the generation units, the electricity demand is the basis of the problem to be solved by the power systems, where its planning and operation revolve around being able to supply in a good way the consumption of the different users that are present on the grid.

Electricity demand in traditional system operation is used as an input to the problem that does not consider the possibility of being modified for further cost minimization, however, with the transition to smart grids that paradigm has been changing and electricity demand is increasingly active in system operation, having the possibility to participate by changing consumer behavior, which is known as Demand Side Management (DSM) [12].

To achieve this behavioral change, the necessary communication resources must be in place [12], for the demand to communicate with the system so that it receives signals and can send responses associated with demand control, which will be addressed in Section 2.3.

2.2.1. Electricity Demand as a Control Variable

DSM, as its name suggests, works on the management of the power consumption on the demand side, so power consumption becomes a control variable in the power system when DSM is applied. By considering the electricity demand as something controllable within the system, it is possible to adjust the behavior of the demand in order to minimize the operating cost, on the other hand, it can also contribute when contingencies occur in the system, or be used to minimize the waste of solar energy, among other uses.

Usually the daily electricity consumption curve has a predictable shape given the behavior of the users, where in the early hours of the morning consumption begins to grow to coincide with the start of the day by the population, using kettles, lights, stoves, radios, etc. Then, the curve continues to grow until it declines in the beginning of the afternoon, in the middle of working hours. The curve remains with values close to the consumption mentioned above, and reaches its peak in the late afternoon hours when workers return to their homes, since is there where the different types of appliances with high energy consumption are most used. Finally, energy consumption decreases at the end of the day.

The curve described above, for the Chilean case, can be obtained from [13], and this curve is the one to be controlled by the DSM, so that it adjusts to a new curve considered optimal by the system operator. On the other hand, to demonstrate the change that can be obtained by controlling the demand, in [14] is shown how the consumption curve is adjusted, so that the peak demand is eliminated, which could be applied in a demand profile to reduce the operating cost.

2.2.2. Elasticity of demand

Although demand may be controllable from the DSM, it must be considered that consumption may not always be adjusted to what the operator wants, because behind the consumption there are users who seek their own optimal demand profile based on their needs, whose objectives may go against what the operator wants. This is why the concept of elasticity of demand appears, which combines psychology, sociology, anthropology and economics, and attempts to decipher users decision making, either individually or in groups [15]. In [16] elasticity is defined as the ratio of the relative quantity variation over the relative price variation before and after DR (equation 2.1).

$$e = \frac{\frac{\Delta Q}{Q}}{\frac{\Delta P}{P}} \tag{2.1}$$

The aforementioned behavioral change is achieved through user incentives, which, depending on the flexibility of the users, modify their consumption at times when the system operator requires it. The level of user flexibility is difficult to determine as each user reacts differently [3] and depends on multiple variables [17] [16].

In [15] the customers are summarized in three types shown in Figure 2.1, which shows a pyramid where the base is customers with low flexibility, and the top is highly flexible customers, giving also a notion of how many customers are currently willing to modify their consumption. It is important to note that demand elasticity is one of the big challenges in smart grids, having to deal with the uncertainty of users reaction to incentives [3], along with all the information management needed to take advantage of users consumption flexibility.

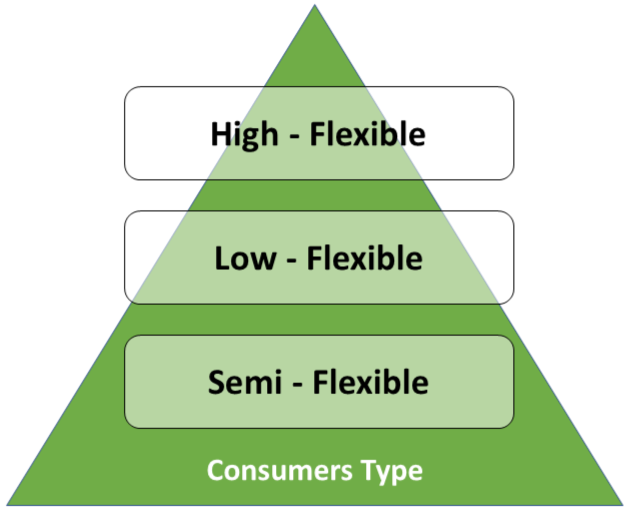


Figure 2.1: Types of customers according to their flexibility (adapted from [15]).

In the model used for the study, the elasticity of users is expressed in terms of the relevance given to their welfare. This relevance given to the welfare is defindeb by the user and becomes a parameter of the optimization problem to determine the consumption of the user. Depending on this parameter, a consumption profile is determined that will respond in different ways to the price signal based on the importance given by the user to his welfare. It is also important to note that the model considers the appliances owned by each user and the time ranges in which he is willing to use them. Considering this, each appliance is also associated with the relevance it has for the user, allowing to differentiate the flexibility of each different appliance, either in their consumption or in the hours that they are used.

2.3. Demand Side Management and Demand Response

The basis of the studies carried out is the participation of the demand side for the operation of the grid through the DSM. Being this the application in charge of linking the system operator and the users so that the operation of the system is optimal including demand now as a variable capable of being controlled by means of incentives. The definition of DSM considered for the purposes of this thesis is as follows [18]:

- *"The term Demand Side Management refers to a group of actions designed to manage and optimize a site's energy consumption and to cut costs, from grid charges to general system charges, including taxes."*

The above definition is provided by *Enel X*, a company that has promoted and led the inclusion of DSM in power systems. In the above definition the optimization of energy consumption can consider different objectives such as *Peak Clipping* or *Load Shifting* [2], which are addressed in section 2.3.3.

The use of DSM implies a relationship between the demand side and the supply side that provides a benefit to both actors, so that in addition to being favorable for the system, it is favorable for the users of the distribution system, where the consumer, if he has tools for price forecasting (which can be complemented with other resources such as energy storage or solar generation) can modify his consumption in the hours of high price by moving it to other hours where is more convenient for him. Is in this interaction where the operation of the system is improved, since the system indicates to the users in which blocks of time is more convenient for them to consume through the price of energy, and the user responds based on its elasticity.

The above-mentioned interaction can be carried out through two types of programs [3]:

1. Energy efficiency improvement programs: They seek to reduce the amount of energy required.

2. Demand Response (DR) Program: Temporary and optional adjustment in reaction to price signals or reliability conditions. It has been demonstrated that with this program, increasing the demand side management capacity decreases the total cost, and regularizes the price in peak demand hours.

The focus of this thesis is on DR programs, studying what happens in the system when users do not behave as committed. Two categories have been defined for the DR programs where each has different sub-categories as shown in Figure 2.2 [3] [19] [20].

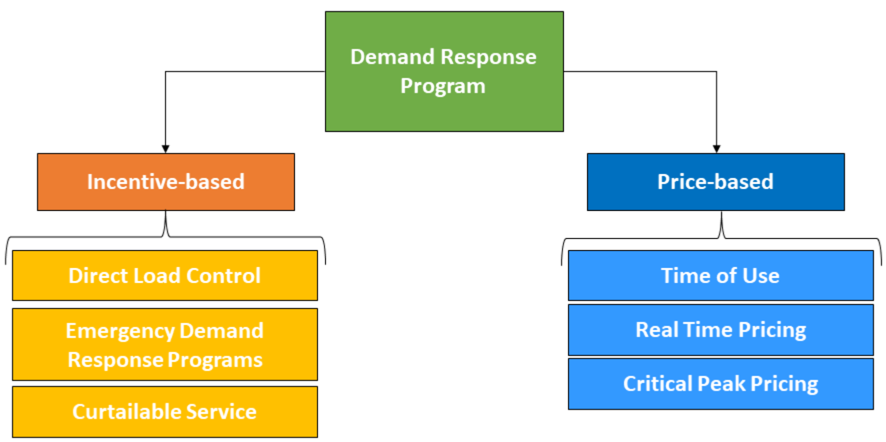


Figure 2.2: Categories of Demand Response Programs (adapted from [3]).

The implementation of the DSM through these programs brings benefits to the system, however, the complexity of its implementation brings with it multiple challenges and obstacles to achieve it. The main one is communication between the demand side and the supply side [3], which is addressed in section 2.3.1. On the other hand, the obstacles are:

- Consumer behavior: It is necessary to know or approximate how users will react to these programs, so that the consumption curve can be predicted and the system operation can be determined accordingly. Not knowing the behavior of the users could result in the operation of the system using DSM being more costly than one without using this tool, by having a wrong consumption forecast that could lead to the need to turn on emergency machines to avoid loss of load, or in the opposite case, a consumption so low that makes it necessary to dump generation.

Due to the above, is necessary to study what happens when user behavior is not as expected and, if necesary, to define a model or methodology to forecast the demand profile of the users that make up the grid based on the incentives provided by the system, which, taken to the residential level, implies a multidisciplinary work where engineering sciences and sociology must study user behavior to find an adequate solution to this obstacle.

- Data issues: The lack of experience in DSM makes it difficult to obtain the necessary data for its correct operation. Once this use becomes widespread, is expected that this will cease to be a problem. However, at present it is a major barrier, an example of this is the Chilean case, where there is currently an aversion to the use of smart meters, which provide information to the system operator and allow sensing of user consumption data with greater accuracy.
- Customer baseline (CBL): The success of the DR Programs is calculated using the customer baseline, which indicates the expected consumption of the users without considering demand management, and an error in the way of calculating, in addition to incorrectly measuring the effects of the program, may also imply a lower participation by the users [21].

The challenges mentioned above are just some of the issues of the DSM. Figure 2.3 illustrates the link between all the challenges, such as the data issues generated by the lack of knowledge of the user's behavior, which in turn triggers more problems for the DSM.

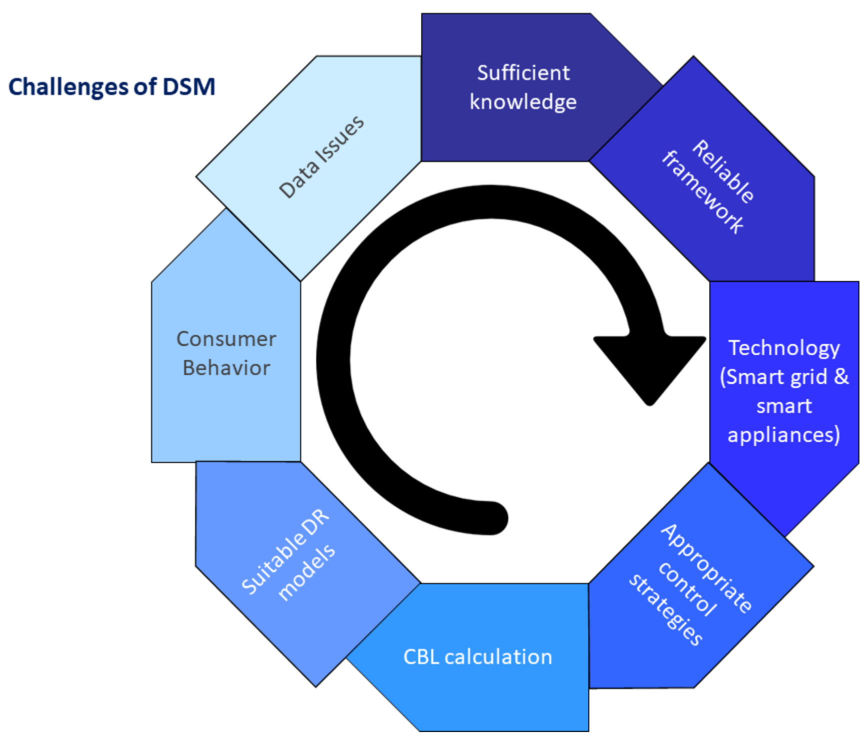


Figure 2.3: DSM Challenges (adapted from [3]).

From the above is evident that the lack of knowledge of user behavior generates a chain reaction that can be very detrimental to the system in both technical and economic terms. This is because the lack of knowledge of the user's behavior implies, among other things, a real demand profile different from the expected one and/or deviations in the consumption caused, which in aggregate can generate an impact on the operation of the system, which is what is studied in this thesis.

The aforementioned lack of knowledge of user behavior, or their response to DR Programs is caused by the complexity of classifying users according to the information available to the grid operator, an example of this is given in [20], where is mentioned that houses of similar size, occupied by demographically similar families, with a similar set of appliances and under the same geographical condition vary their electricity consumption by up to 200 %. Linked to the latter, [4] discusses the different tolerance levels of users to DR programs and how these affect their response to incentives. In addition, in [22] they conclude that "...the residential sector consumption seems to be characterized by variability and change, with human behavior playing a central role in both the short term and long term initiation, maintenance and alteration of energy flow".

On the other hand, [20] highlights price unresponsiveness as an important issue in residential demand response. The latter is associated with the indifference of some users to the price signals they receive from the DR program, as shown in [23] where a study conducted in California showed that, out of a sample of 1300 households, 44 % did not respond to the price signals, which shows that even if users have the information needed to participate in a DR program, there is no guarantee that it will act as expected. In addition, equity issues must be considered, where users with a more disadvantaged socioeconomic situation take less advantage of the DR Programs because they cannot reduce their consumption considerably as it is already reduced to reduce the electricity bill, which implies a lower effectiveness of the DR Programs in these situations.

In addition to the challenges, the opportunities that DSM brings to other elements such as renewable energies must be considered. The presence of this type of generation means greater uncertainty in the system, in addition to having lower reliability and controllability compared to conventional generation. These difficulties can be addressed in many ways, being DSM one of the main ones as it is the most efficient and cost-effective approach among multiple solutions such as renewable generation forecasting, or connection to nearby grids [24].

2.3.1. Enabling Technologies

For the implementation of the DSM and DR programs in the electrical system, certain technologies are needed to enable its operation. The collection of information, actuators on the loads and the network of the resources that are being controlled are of vital importance for the DSM, without technologies that allow it could not work correctly. The following is a brief explanation of the technologies that enable the use of DSM according to [25].

2.3.1.1. Smart Meters

Smart Metering is one of the most relevant systems for Smart Grids and in particular for the correct operation of DSM and DR programs [26]. Smart Metering uses Smart Meters to operate, this device collects detailed and real-time information on energy consumption or generation and sends it to the operations center of the distributor in the case of the DR.

In addition to providing information on energy consumption and generation in real time, it also measures voltage, current and power factor levels, so that an eventual demand management can also consider these variables to avoid frequency or voltage instabilities. The data that these devices deliver are those used in the electricity market, so smart meters are considered as the basic devices for the DSM or DR system, being essential for tools such as Smart Billing [27].

2.3.1.2. Smart Plug, Smart Thermostat and Smart Appliances

As a complement to smart meters, the Smart Plug is also vital for the implementation of automatic or manual DR, as it acts as a bridge between the equipment to be controlled and the Internet of Things. It provides information on the RMS value of current, active and reactive power and the angular phase shift between current and voltage [28].

Smart plug is the main tool for load disconnection, which can be automatic or manual, in the first case the smart meter determines from the user's preferences and the energy price which devices to disconnect using the smart plug. From this it can be inferred that the smart plug is something that should be complemented with smart meters for DR [28]. Figure 2.4 illustrates the operation that can be given to smart plugs, which connected to a router can be controlled by a smartphone either automatically or manually from the price signals received.

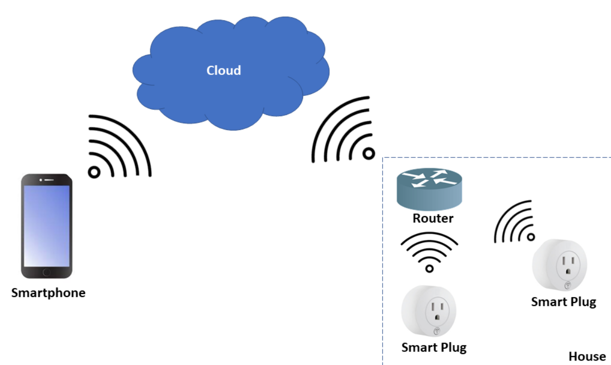


Figure 2.4: D-link Smart Plug (adapted from [28]).

On the other hand, there are the Smart Thermostat and Smart Appliances whose operating bases are the same as those of the smart plugs, but instead of controlling the switching on and off of devices, they manage the temperature and automate and control household appliances respectively.

2.3.1.3. Internet of Things and Cloud Services

DSM is part of the Smart Grid, which in turn is part of the Internet of Things (IoT), through the so-called Internet of Energy (IoE) [29]. The IoT is necessary for the effectiveness of DSM and DR as managing demand mainly in the distribution network requires networking, and as stated in [29] the IoE aims to “optimize the efficiency of the energy infrastructure by creating a distributed network of sensors and power generators”, which largely coincides with the objective of DSM.

Having a network of devices (smart plugs, EVs, smartphones, smart appliances), the IoT gives the DSM the possibility to create a network so that management can be done on a massive scale. Based on the above, the IoT can be considered as the backbone that links all the nodes participating in a DR program.

Along with IoT, cloud services are also necessary for the implementation of DR. The network in which, thanks to IoT, devices participating in DR are located are connected to the cloud, and support for algorithm execution, data analysis and databases is provided there [30].

2.3.1.4. LAN/HAN/WAN

To be part of the demand management, the devices to be controlled must be grouped according to user/home/building. Prior to connecting to the cloud, networks must be established within the location where demand management is desired. If a house has smart devices but does not have a LAN to access the network, the control of its devices is limited as it cannot receive price or status signals from the network.

Since demand management can be performed in different types of buildings, networks can range from a Home Area Network (HAN) for residential DR [31], to a Wide Area Network (WAN) for the case in which the management is performed in different areas of the same company .

2.3.1.5. Advanced Metering Infrastructure (AMI)

An important part of smart grids is the AMI, which, through the control and communications it facilitates, allows interaction between the user and the electrical system.

In [26] it’s stated that it does not consist of a single technology, but encompasses several of them to meet the AMI objective (some of them already mentioned as enabling technologies), these are: Smart Meters, Home Area Networks, integrated communications, data management applications and standardized software interfaces. Through these technologies, AMI provides both users and operators with the necessary information to manage demand and meet the objectives of the DR.

2.3.1.6. Wide Area Monitoring System (WAMS)

This technology allows monitoring the status of power systems in real time through phasor measurement units (PMUs), and one of its objectives is to improve the stability and reliability of the network [32].

For the DSM or DR Programs this use is the one that collects the information used to determine the price signals to be sent to the users, it is in charge of detecting problems with the voltage or frequency of the network, which are directly related to the level of demand of the network. The WAMS delivers information on the state of the network to the operator so that it - together with the rest of the information - can make the best decision regarding the amount of demand to be managed, in addition to other variables such as dispatch, use of spinning reserves, etc.

2.3.2. Communication Protocols and Standards

As a complement to the enabling technologies described above, it is also necessary to establish communication protocols to achieve a good exchange of information between loads (or load aggregation) and the distribution system operator.

Since DSM, and therefore DR, is not yet a mature technology in electrical networks, there is no single protocol defined for the communications involved; however, there are several of them that are useful for DSM and DR Programs, some of them are IEEE 2030.5 standard, and OpenADR.

2.3.2.1. IEEE 2030.5

This standard defines the application layer, using the TCP/IP protocol in the transport and network layer, to manage the end user's energy environment, including the DR and DSM. This standard defines the mechanisms for the exchange of application messages, the exact messages, including errors, and the characteristics associated with the security used [33].

In [33] the following is stated: "*This standard focuses on a variety of possible architectures and usage models including direct communications between a service provider and consumers/prosumers, communications within a premises or home area network (HAN), and communications between a service provider and an aggregator.*". From this it can be inferred that this protocol is of great utility for the DR, as it allows the flow of information to consumers and smart devices, which can be price signals, measurements or response to load control.

In terms of interoperability, this protocol uses the REST architecture, and is based on the use of GET, PUT, HEAD, POST, DELETE actions. Any application protocol capable of implementing RESTful commands could be used with the IEEE2030.5 standard.

2.3.2.2. OpenADR

Unlike IEEE 2030.5, this standard focuses solely on demand response. OpenADR is described in [34] as an open and interoperable information exchange model and the objective of this model is to simplify DR for the energy industry through price and load shifting signals that allow the end user to modify their consumption pattern, lowering their costs and system costs, and improving energy efficiency.

The exact definition of OpenADR is [35]:

“Open Automated Demand Response (OpenADR) is an open and interoperable information exchange model and emerging Smart Grid standard. OpenADR standardizes the message format used for Auto-DR so that dynamic price and reliability signals can be delivered in a uniform and interoperable fashion among utilities, ISOs, and energy management and control systems.”

Its usefulness for DR is evident from the definition, being also used in multiple systems in the world with good results. Given these good results and good projection, it is expected to become an international standard (IS) of the International Electrotechnical Commission (IEC).

Its architecture is based on two types of nodes, called Virtual End Node (VEN) and Virtual Top Node (VTN). In [35] it is stated that the VTN is a server that sends price or load signals to end devices or intermediate servers, while the VEN is a client that can be an Energy Management System, a thermostat or any end device that accepts OpenADR signals. In [36] the interaction between both nodes is simulated using VOLTTRON, where the VTN sends events to the VEN through a web platform and the VEN responds by adjusting its demand (in the example storage is managed), generating changes in the demand, load or power curves supplied by conventional generators. All these changes have considerable impacts on system costs, evidencing the usefulness of OpenADR for the DR.

These nodes are organized in different architectures, figure 2.5 shows an illustration in which [35] shows an example of architecture for DR in which OpenADR is used, it is important to note that there are multiple possible architectures which are detailed in [37], some of them are: Basic Two-Tier Architecture, Two-Tier Architecture with XMPP, Basic Three-Tier Architecture, Hybrid Device Deployment Architecture and Vendor Cloud, etc. We must note that that between nodes there is no peer-to-peer communication [38], i.e., there is no direct communication between VTN nodes, or between VEN nodes, so that in each interaction one node is defined as VEN and another as VTN, similar to a communication between client and server, giving the possibility that the same node acts as VEN or VTN, as would be the case of an aggregator (figure 2.5).

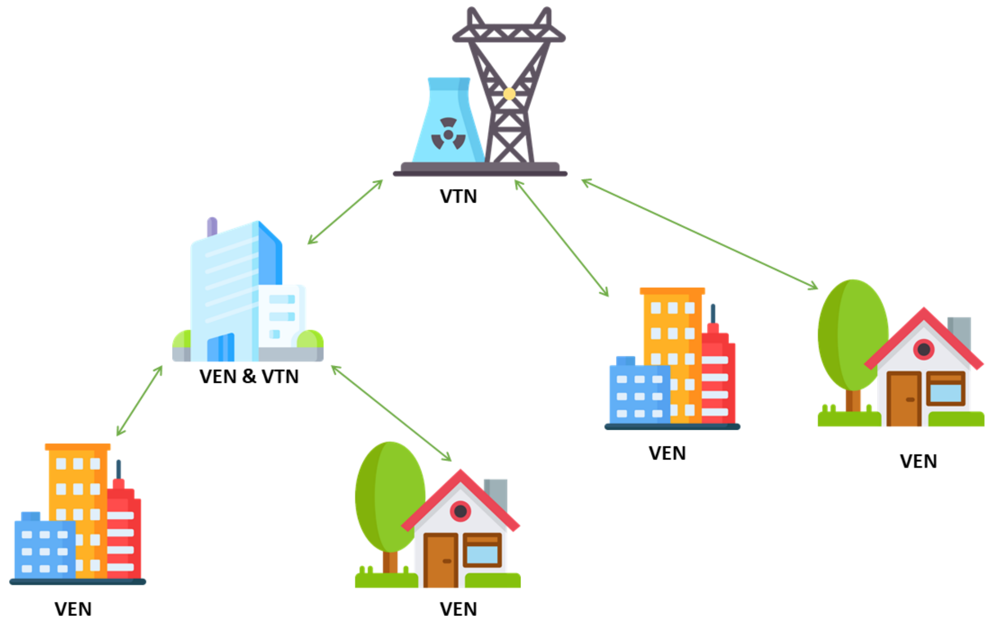


Figure 2.5: Example architecture for OpenADR (adapted from [35]).

In [38] the architecture used by OpenADR is studied by defining three layers shown in the figure above, these are: Demand Response Service Provider (usually the distribution company) as the VTN, the load aggregator as the intermediate layer (VTN/VEN), and the end users (VEN) that receive the signal from the DR Program. These layers provide a hierarchical structure to the architectures where OpenADR is used, as shown in Figure 2.6. It is important to note that the communication between the loads and the load terminal generally does not use OpenADR, and can be via ZigBee, Modbus or other technologies for signal acquisition and remote control.

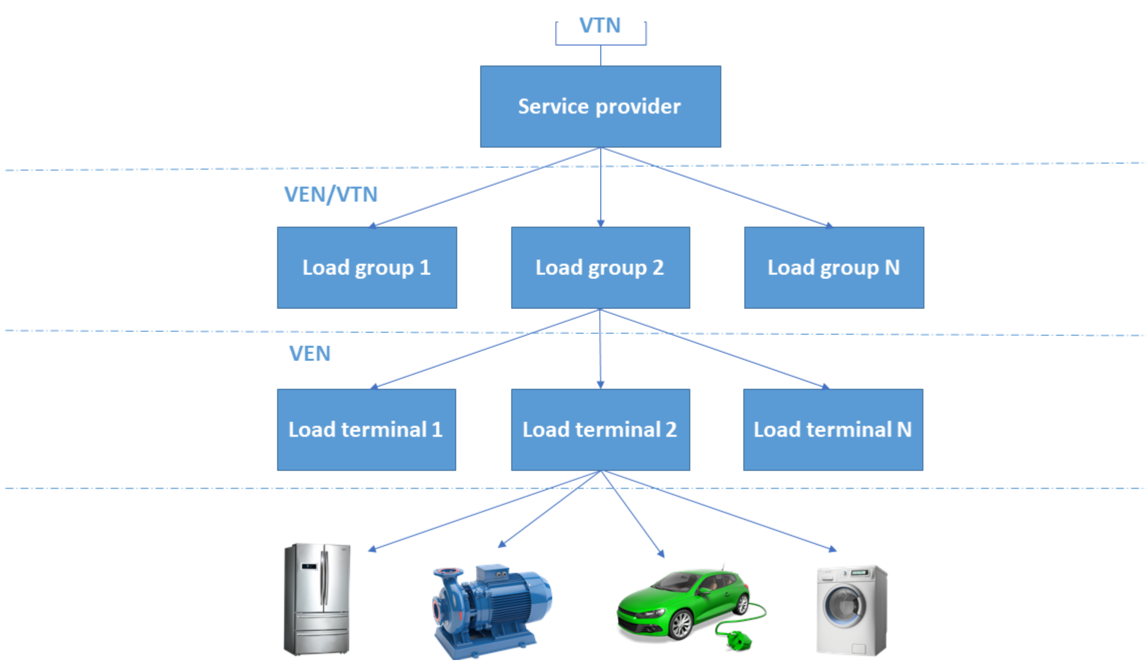


Figure 2.6: OpenADR hierarchical structure (adapted from [38]).

What kind of information is needed for the DR Programs?

Based on the enabling technologies and information protocols required for the implementation of DR, it is possible to determine what type of information is necessary for it to operate correctly.

Based on the OpenADR model, will be talked about VTNs and VENs for information flow. Based on the enabling technologies and the objective of improving grid stability, the information provided by smart meters is the basis on which the operator (VTN) makes its decisions, since most of the information needed for the DR is the one that allows knowing the real-time status of the grid, such as consumption, voltage, current and power factor of each load terminal.

From the information collected from all the smart meters it is possible to know the state of the network, then, based on this information the operator makes decisions on DR. Once the desired change of state of the network is determined, the operator sends to the load terminals (which can be houses, shopping centers, offices, etc.) the information that seeks to generate a response in its consumption, which in the standard are defined as "events". Considering that the work is done with OpenADR, these signals are related to energy prices or load changes, each type of signal can be delivered in different formats [39]:

- Price signals: These are received by the customer in order to adjust its energy consumption, they can be energy price signals in some interval, either through the price itself, a price difference or a multiple of the reference price. According to the above, the types of price signals are:
  - *Price Absolute*
  - *Price Relative*
  - *Price Multiple*
- Load signal: When the DR is automated, the operator can send signals to directly manage the user's load, for that it sends signals that modify the state of the loads to achieve the desired consumption adjustment, this can be through smart plugs, smart thermostat, smart appliances or any device capable of being remotely controlled by OpenADR. As with the price signals, these can be sent in different formats, which can be focused on modifications of the load percentage, or of a specific value. According to the above, the types of load signals are:
  - *Load Amount*
  - *Load Percentage*

Scalability: Does OpenADR scale well?

Its website mentions that one of its features is its scalable architecture: *"Scalable Architecture - Provides scalable communications architecture to different forms of DR programs, end-use buildings, and dynamic pricing"*. From this it can be inferred that this standard is capable of being implemented in both large and small systems.

How do nodes communicate in OpenADR?

In [40] the communication architecture of OpenADR is described. Communications are through the Internet via APIs. This communication is through an OpenADR server interface called Demand Response Automation Server.

2.3.3. What can be done with the DSM?

From what has been previously stated in the report, the purposes of DSM and DR programs are evident, being the most important of them the reduction of peak demand. To achieve this and the other objectives, there is no single way of approaching the problem, and six DSM techniques are identified [2]:

- (a) Peak Clipping: It consists of load reduction during periods of high demand, thus reducing the duration of the peak. This is achieved through the shutdown of consumption equipment and the use of distributed generation.

- (b) Valley Filling: Promotes consumption at hours that do not correspond to peak demand through incentives, in order to encourage consumers to change their consumption habits.

- (c) Strategic Conservation: It seeks to reduce energy consumption through energy efficiency by reducing energy wastage, therefore an important part of this technique is to encourage technological change.

- (d) Strategic Load Growth: It seeks to control the increase in energy consumption, for which the operator uses intelligent systems, energy-efficiency devices or more competitive energy sources.

- (e) Load Shifting: It shifts part of the demand from peak hours to off-peak hours, modifying the demand curve but without modifying total consumption.

- (f) Flexible Modeling: It consists of actions defined in a plan between the consumer and the energy supplier. It seeks to limit the consumer's energy use at certain times through load-limiting devices.

2.3.4. Enerdis DR Scheme

As discussed above, there are different schemes for DR programs. The scheme used by Enerdis is price-based, seeking to incentivize consumption during the hours of maximum renewable generation. By focusing users consumption on these hours, the aim is to maximize the benefits of renewable energies, particularly solar, and reduce users electricity bills and system operating costs, thanks to the low operating costs of these technologies.

For the implementation of the DR program that Enerdis aims to implement, the price signal will be generated from the system information in a way that meets the objective of minimizing user and system costs. Once the user receives the price signal, he will register through the Enerdis platform his list of manageable and non-manageable appliances indicating the relevance of each one and the importance that the user will give to their welfare over the price signal on the day. With the information of the appliances and preferences, the optimal consumption profile for the user is calculated. Once the user confirms his consumption profile, the information is sent to Enerdis, which delivers the information to the system operator. If the above process is carried out massively, it is expected to generate an impact on the grid, produced by the change in multiple users in their consumption, so that it moves to hours in which they take advantage of a greater amount of renewable energy.

Compliance with the promised demand profile can be achieved automatically or manually. If the necessary technologies for automation are available, this can be achieved through OpenADR by managing the user's appliances through the IoT according to their consumption promise. However, Enerdis also aims to provide the option of performing demand management manually, considering that most of the residences currently do not have the necessary technologies to automate the management. However, it is important to note that regardless of whether the management is automatic or manual, there will be room for non-compliance, since in both modalities the user can modify his consumption profile if he wants.

It is important to note that since in Chile it is currently not possible to implement a tariff for residential users through a price signal, Enerdis decided to start focusing on users who own residential solar generation, since these users can obtain economic benefits through demand management. On the other hand, users who do not have solar generation could not obtain economic benefits by having a regulated tariff, however, these users are also expected to participate in demand management proposed by Enerdis since one of its main objectives is the reduction of CO_2 emissions. This objective is also of interest to the population given the increased importance of the climate crisis in recent years, where renewable energies are seen as a good measure to reduce emissions [41].

2.4. Type of Loads

For residential demand management, work is done with different types of loads, which are classified according to their flexibility [3] [42]:

- Non-flexible loads: These are used at certain times that cannot be modified from demand management.
- Flexible loads: The hours in which these loads are used can be adjusted, changing from one hour to another within the ranges allowed by the user. Within the flexible appliances there are three subcategories [6]:
  - Non-interruptible appliances: Loads whose use is continuous, i.e., once they start to be used, their operation must not be interrupted.
  - Interruptible appliances: Those that can divide their consumption into different blocks throughout the day, which may or may not be consecutive.
  - Thermostatically controlled appliances: These devices operate all the time and what is managed is the temperature that is set in them, seeking to reduce costs considering the importance that the user gives to their well-being.

It is important to note that within the literature there are different classifications for the same appliances that may be available in a house [6] [43]. From the above we should note that there is no single category for each appliance and each scheme can use the classification it deems appropriate.

2.5. Economic Dispatch

The main objective of the economic dispatch is to minimize the variable generation costs and to minimize the active power not served in the system loads. In order to meet this objective, it is decided which generators will operate, at what time they will operate and how much active power they will deliver [44]. In order for the above to occur, economic dispatch considers two main axes [45]:

- Unit commitment
- Dispatch of generating units for today

2.5.1. Unit Commitment

The unit commitment is the determination of the compromise that each generating unit will have in each time slot within which the system operates, i.e., it indicates in which time blocks each unit must be on or off considering the different system restrictions.

The unit commitment has the main objective of minimizing system operation costs, while complying with the restrictions associated with the security and correct operation of the system [46], this problem can be solved in multiple ways such as Priority Listing, Dynamic Programming, Integer and Linear Programming, among others.

For this cost minimization, the cost functions associated with the different machines in the system must be considered, so that those that can meet the grid requirements at a lower cost are prioritized. On the other hand, the parameters of the network, such as the reactances of the lines together with their flow limits, as well as the different demands present in each bus, must also be considered.

Since the unit commitment is carried out considering a time horizon, it must be performed based on an estimation of the demand within the next time slots, so that DSM has a direct impact on the resolution of the unit commitment problem [47] [46]. By providing greater controllability to power consumption, this advantage can be used for cost minimization through load shifting, peak saving or others.

The impact that the DSM or DR programs can have on unit commitment depends on the time horizon over which it is being implemented. If the DR program to be implemented considers a time horizon of weeks, it will be able to influence the unit commitment. However, if the demand management considers small time horizons, it will not be enough information to participate in the unit commitment because it does not work with the same time horizons. An example of this is the "Emergency Demand Response Program" [48].

The impact of DSM on unit commitment has been studied recently. In [47] it is concluded that the system operator acquires noticeable profits with the implementation of DSM. One of the contributions of [49] is to show that when considering DSM in unit commitment, the system operator perceives a greater reduction in demand than actually possible, due to a possible underestimation of the demand shift. In [50] a system is simulated in which the limits of the amount of demand that can be managed are found considering the effects that this will have on the voltage levels of the different elements of the grid.

2.5.2. Dispatch

In [51] economic dispatch is defined as a subroutine of the unit commitment problem whose aim is to locate optimal generator outputs such that the entire load may be supplied in the most economical way. In [45] it is mentioned the daily dispatch of the units, this part of the dispatch is in charge of the real time operation of the system, so it is directly related to the unit commitment from which it receives information. Once the unit commitment has been made, the hours in which each generating unit must operate, independent of its setpoint, have been defined. Then, for each hour or time slot considered by the dispatch, depending on the state of the grid, it must be determined how much power each generating unit dispatches in order to maintain the balance between generation and consumption [45].

In order to maintain the balance between generation and consumption, real-time monitoring of the grid status and the use of Automatic Generation Control are considered. The above in order to keep the network operating within safe ranges. To achieve the above, and going beyond cost minimization, some of the tasks that the dispatcher has are [45]:

- Monitoring of generation and consumption to ensure energy balance.
    - Maintain the frequency at the set value (50 [Hz] or 60 [Hz]).

- Hourly monitoring of the dispatch program to ensure that the balance is maintained during the next period.

- Monitoring the flow through transmission lines.
    - Maintain the flow through the lines within the allowed limits.
    - Maintain voltage within allowable limits.
    - Take corrective actions
        - Change the dispatch
        - Load shedding

The aforementioned tasks aim, in addition to maintaining balance in the network, to ensure the safety and adequacy of the system. When any of these features fails, there is a higher probability of incurring in load loss, which generates a negative impact on network users, resulting in a failure cost or a Value of Lost Load that penalizes these undesired events in the network.

2.5.3. Enerdis Scheme

The demand management that Enerdis aims to implement considers a horizon of one day. This time horizon was chosen because residential users will hardly be able to deliver a consumption promise with longer time ranges, as it is complex to determine which appliances will be used, or at what time it will be more convenient for the user. An example of this is the use of an electric vehicle one week in advance: It is difficult to determine whether it will actually need to be charged and, if so, at what time will be most convenient. When considering a one-day horizon the effects of demand management will be on the daily or real-time operation of the system, and in principle no involvement in operation planning is expected.

2.6. Value of Lost Load

In the event that the dispatch does not provide the machines to supply the total consumption due to an erroneous demand forecast or contingencies, one of the system's alternative to maintain the system balance and avoid the occurrence of a blackout is load shedding.

Load shedding does not explicitly imply any cost, as does the cost of fuels or operation and maintenance costs; however, it does generate an impact on the grid because the objective of the system is no longer being fulfilled. For this reason, a cost is associated to load shedding to penalize the occurrence of these events that directly impact customers and generate safety problems in the grid.

This cost is known as Value of Lost Load (VoLL) and indicates the average cost of the accidental interruption of 1[MWh] of an electricity consumer [52]. The value that VoLL can take is variable and it is not possible to determine it physically, so it is usually estimated from consumer surveys, which is why VoLL is very variable as it depends on the type of customers (residential or industrial, for example), the time of day in which the outage occurs, among others.

Given the aforementioned drawback, other alternatives have been used to manage load shedding when performing power system studies, such as the use of a fault generator. This alternative is used in [53] when simulating a power system, where in addition to considering consumption and generation at the system buses, fault generators are included for cases where it is not possible to achieve the balance between demand and generation, making the solution of the problem infeasible.

2.7. Distributed Energy Resources

On traditional grids, work is done considering centralized generation with machines capable of generating large levels of power to supply the demand considering a unidirectional flow, however, the advance towards smart grids has given rise to new types of generation such as distributed generation through distributed energy resources (DERs), which has advantages such as the reduction of costs associated with energy transmission, or an increase in energy efficiency [54]. This paradigm change is also driven by the current climate crisis, since distributed energy resources are less polluting than conventional generation, and [54] mentions that the increase in energy efficiency achieved through distributed generation reduces CO_2 emissions.

In [55] DER are described as electric power generation resources that are directly connected to medium voltage or low voltage distribution systems, rather than to the bulk power transmission systems. These power generation resources include storage and generation units.

As mentioned above, one of the main drivers of DERs has been the climate crisis and the interest in moving towards a more sustainable system. The contribution that the DERs provide in this aspect is, in addition to the reduction of emissions achieved through energy efficiency, a greater inclusion of renewable energies in the system, such as solar and wind energy that also helps to reduce the emissions of CO_2 [41].

As a counterpart to the benefits that DERs bring, their inclusion at the same time implies challenges in the grids in which they are implemented. By including distributed resources, the system must be able to support a bidirectional flow of power, since with DERs there is the possibility that the buses defined as consumption buses supply energy to the system, as could be achieved through residential solar generation, or the use of energy storage systems. In addition, if the penetration level of renewable energies is very high, the security of voltage levels at the buses must also be guaranteed, considering the voltage increases that can be generated at times with high solar generation.

2.8. Net metering

For residential generation, different schemes are considered for the payment or billing of energy, such as net billing, feed in tariff or net metering. For the studies carried out, the net metering scheme is considered, so this section briefly explains what it consists of.

In [56] net metering is described as an electricity policy that allows users to partially or totally offset their electricity consumption from residential generation. This is achieved by metering the energy flow in both directions.

To measure the energy flow, a meter that is capable of rotating in the two possible directions is used, where the meter increases when a customer is drawing power from the grid, and it decreases when the customer is sending power to the grid. Another alternative is to separately measure both flows and then subtract accordingly. With these measurements, at the end of the month the user pays for the net electricity used, i.e. balancing the energy injected and absorbed from the grid.

2.9. Discussion

In this chapter the most relevant concepts were reviewed in order to understand the experiments carried out in this thesis, meet the objectives, and validate the established hypothesis. From the previously exposed background, the importance of user behavior for the correct performance of demand side management becomes evident, standing out as one of the main challenges of this new tool, originated by the complexity of modeling and predicting user response in demand management.

Therefore, this thesis seeks to address this problem by analyzing the impact that the lack of knowledge about users can have on demand management, in particular the uncertainty regarding the compliance with the DR program. For this purpose, different scenarios are simulated in a electric system, where the different users have a behavior different from the expected one, expressed through changes in the parameters that determine their consumption curve.

2.9.1. Why is non-compliance worth studying?

On the one hand, the study of the impact of non-compliance in demand management is necessary to verify that the use of DSM is convenient for the grid, since deviations in the demand curve may increase operating costs or even reach consumption levels where it is not possible to supply all the demand, or non-renewable generation must be shed. The possibility of deviations in demand management is discussed in [42], where it is mentioned that any deviation is undesirable for the grid.

On the other hand, it is important to note that the user's response behavior is variable and has a correlation with the timeline, and to be part of the energy market it is necessary to have an accurate prediction of user behavior. Without this correct prediction, participation in the market will be affected by changes in the consumption curve of the users, where despite having defined a certain consumption, the user may behave in a completely different way than expected, so it becomes important to study the non-compliance in order to find ways to address it in the models, if necessary.

On the other hand, as electrification rates increase, a higher percentage of users' energy consumption will be through electricity (in particular in Chile a growth rate of 2.28 % per year is expected [57]), which will increase the set of manageable devices, which may also modify the preferences of their other devices. By increasing the number of manageable devices there will be a larger space to perform demand management [57], but as a counterpart there will also be a larger space for non-compliance which will generate an impact on demand management.

Another aspect to be analyzed is the increasing penetration of ICTs. ICTs have a great potential to be used in demand management, but also they pose challenges such as unifying the communication of heterogeneous devices within a residence, or the uncertainty to what extent the user will allow to automate their consumption, even if they have previously defined their preferences. In this last point there is a link with non-compliance, since the user's elasticity changes according to the environment (temperature, humidity, etc.) in addition to its high variability in behavior, and can even reach indifference to incentives. The aforementioned can affect the automatic participation mechanisms of demand management, since the user has the possibility to cancel the automation through the communication systems, impacting negatively on demand management due to the change in the expected consumption.

2.9.2. Why would the demand management not be fulfilled?

Knowing the relevance of user behavior in DSM, it is important to identify the reasons why a user might not comply with the demand management program. One of the main identified reasons is dissatisfaction [42], since a user with a limited consumption for an established period can switch the demand management in case this management generates a dissatisfaction or undesired effect that was not contemplated at the time of accepting the DR program.

In addition, and as mentioned above, user behavior correlates with the timeline, so that their preferences when deciding how to participate in demand management may be different from those at the time of the management, giving rise to a non-compliance with the DR program due to changes in its elasticity. These changes in elasticity have a direct impact on demand management compliance, as it indicates the importance that the user gives to DSM incentives over other factors such as their welfare. The effect of the surroundings on user behavior should also be considered, variables such as temperature or humidity can affect user compliance, an example of this can be the elasticity of a user in the use of air conditioning, whose values in winter and summer can be very different.

Also, consideration should be given to possible errors in the models for determining consumption, which can lead users to a consumption profile that is not optimal given their preferences, which can lead to dissatisfaction that makes them fail to comply with demand management, negatively affecting the system. Furthermore, errors in the user behavior models should be considered along with errors associated with other factors, such as ambient temperature or solar generation, because if any of these variables does not behave as expected, the consumption profile will be affected due to a consumption profile different from the expected one, despite the fact that the user seeks to comply with demand management. An example of the above is an increase in air conditioning consumption, caused by a higher than expected ambient temperature, which for the system means an unexpected change in the demand curve, despite not changing the target temperature in the user's residence.

Another factor to be considered for compliance is user indifference. As explained earlier in this chapter, whether due to ignorance or disinterest in the incentives of demand management and its benefits for both the system and the user, participation in the DR program is not guaranteed even if the users have the information available [23].

Chapter 3

Methodology

3.1. Description of demand management model

The purpose of this thesis is to analyze how deviations from the behavior promised by users participating in demand management generate an impact on network operating costs. In order to analyze these scenarios, it is necessary to have a model that provides a consumption profile based on the user's preferences and the importance given by the user to his welfare over cost minimization.

Since the experiments are directly related to user behavior, is sought a model that is capable of simulating the change in it. In order to determine the variations that a change on the behavior would imply in the consumption profile and, as a consequence, in the operating cost of the system if this were to occur on a massive scale. For the above mentioned, the pricing-based Demand Response model proposed in [6] was used for the management of the demand, making an adjustment in the power balance constraint. This model consists of an optimization problem that considers two main axes: the user's welfare and the minimization of payments for electricity by the user.

Considering the above, this model receives information from the user, such as personal preferences, devices and their associated information, as well as system information such as the price signal, temperature and expected solar generation for the day. It is important to highlight that the model to be used considers houses with battery systems, solar generation and electric vehicles, without considering the alternative of the latter injecting power into the grid.

Once the model inputs are received, the optimal consumption profile is determined from the constraints and objective function described in the following section. In addition to the optimal consumption profile, other relevant results can be obtained, such as the temperature setpoints or the cost implied by the optimal consumption profile. A block diagram summarizing the above is shown in Figure 3.1.

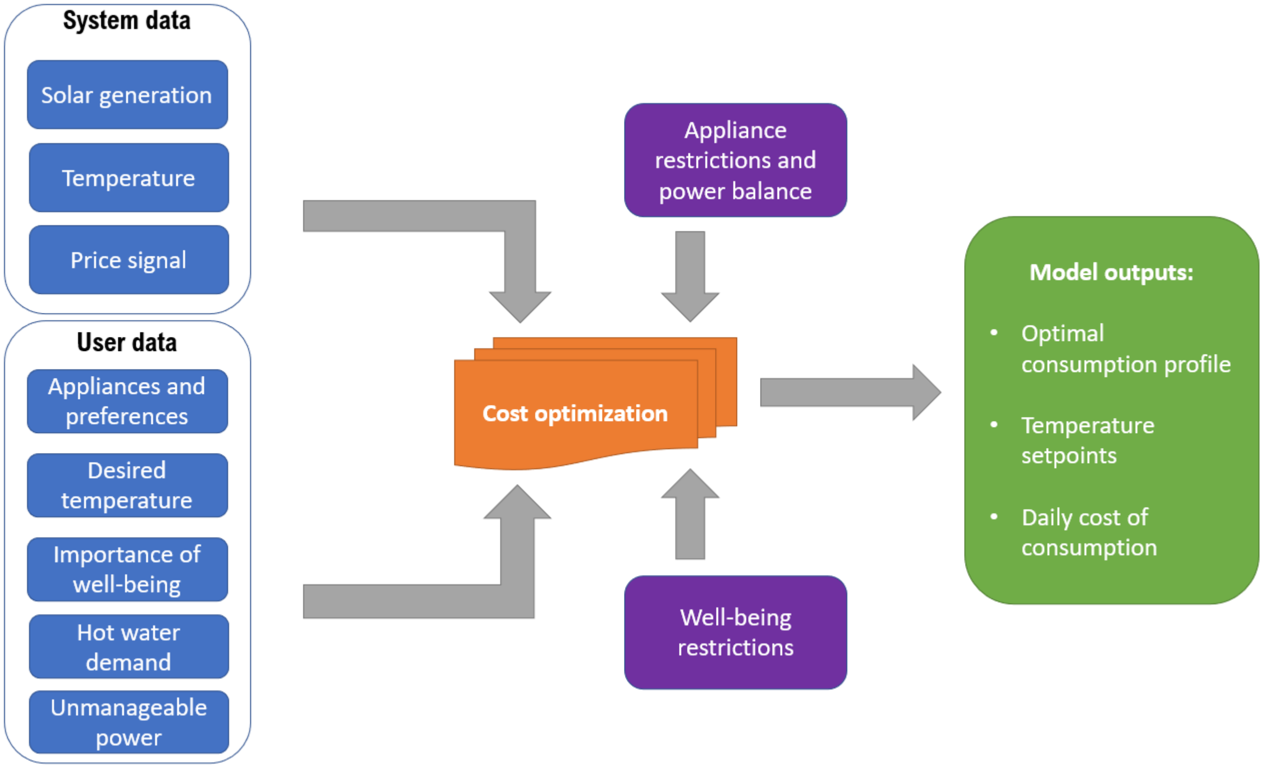


Figure 3.1: Demand management block diagram.

It is important to note that the model being used considers a Net Metering scheme for energy payments, i.e., energy is considered to be sold to the system at the same price at which it is purchased [58]. It was decided to use net metering because [56] indicates that net metering scheme performs better than a feed in tariff when the household electricity bill is taken into account.

Once the demand management model is implemented, the consumption profile promised by the user is obtained, which is used as input for the economic dispatch model.

It is important to note that, considering the definition of [59] the model used for demand management can be considered an agent-based model. The definition of [59] is "ABMs are thus models where individuals or agents are described as unique and autonomous entities that usually interact with each other and their environment locally. Agents may be organisms, humans, businesses, institutions, and any other entity that pursues a certain goal. Being unique implies that agents usually are different from each other in such characteristics as size, location, resource reserves, and history. Interacting locally means that agents usually do not interact with all other agents but only with their neighbors-in geographic space or in some other kind of "space" such as a network. Being autonomous implies that agents act independently of each other and pursue their own objectives.".

Analyzing point by point why the model used can be considered an agent-based model. For the system under analysis, the entities are the users who participate in demand management with the objective of minimizing their costs and maximizing their welfare. Each user is unique as it considers its own set of devices and respective preferences. In addition, local interaction in this case does not occur between agents because the model used does not consider interaction between users; however, if the entity that sends the price signal is considered as an agent, there is a local interaction, which corresponds to the sending of price signals. Finally, each user is considered autonomous because in the model used each one seeks to fulfill only its own objectives.

3.1.1. Objective function and constraints

The demand management model used for demand management is the one proposed in [6] with an adjustment in the power balance constraint. The adjustment was the inclusion of the non manageable power on the power balance. The original model only considers the manageable power, but in a household not all the appliances would be manageable. With the change proposed, the optimal consumption profile will be for all the appliances that the user has, instead of only the manageable ones.

The choice of this model is due to the fact that its formulation allows obtaining different consumption profiles based on the importance that each user gives to its well-being. It makes possible to simulate the non-compliance of the program through modifications in the importance that the user gives to his well-being, modifying the hours in which each appliance is used, or modifying the temperature delivered by the air conditioner or the water heater.

The model to be used considers an optimization problem with two variables that are imposed by the user:

- ω_1: Indicates the relevance given to the minimization of user costs.
- ω_2: Indicates the relevance given to the user's well-being.

The other variables of the optimization problem are described in the Nomenclature section, at the beginning of the document. It is important to note that ω_1 and ω_2 are counterparts to each other, so it must be fulfilled that:

$$\omega_1 + \omega_2 = 1, \quad \omega_1, \omega_2 \in [0, 1] \tag{3.1}$$

Once the values of ω_1 and ω_2 are defined, the objective function of the optimization problem can be written:

$$min\ \omega_1 \cdot J_1 + \omega_2 \cdot J_2 \tag{3.2}$$

Where J_1 and J_2 are the terms that define the cost to pay and user dissatisfaction respectively:

$$J_1 = \sum_{t \in \mathcal{T}} [\lambda_{buy}(t) \cdot P_{buy}(t) - \lambda_{sell}(t) \cdot P_{sell}(t)] \tag{3.3}$$

$$J_2 = \sum_{i \in \mathcal{A}} \zeta_i \tag{3.4}$$

Where the values of λ correspond to the marginal prices of purchase and sale of energy. And ζ_i is the user dissatisfaction caused by the appliance i. ζ_i is different for each user, as it depends on the resentment coefficient ϵ_i that each user defines for his appliances (which is within the next constraints). It is important to note that $J2$ does not have the same dimensions as $J1$, since the latter represents the electricity bill, while $J2$, by measuring user dissatisfaction, cannot be translated into money and is dimensionless.

Once the objective function has been defined, the power to be bought or sold in each hour of the simulation must be determined. To determine the optimum for the user, both physical and welfare restrictions are defined, separating its devices into four types of appliances: interruptible, non-interruptible, thermostatically controlled and non-manageable, where each type of appliance has its own restrictions except for the non-manageable appliances.

3.1.1.1. Non-Interruptible Appliances Restrictions

The restrictions in this section consider devices that, given their nature, cannot or should not be stopped in their operation to fulfill their objectives in a good way, such as a washing machine.

Switching on appliances: Since the user defines the times at which he wants to use his appliances, a restriction must be defined to ensure that the non-interruptible appliances are switched off outside these intervals.

$$P_i^{APP}(t) = 0 \qquad u_i^{APP}(t) = 0 \qquad \forall t \notin [L_i, U_i] \qquad \forall i \in \mathcal{A}_{non} \tag{3.5}$$

Where $P_i^{APP}(t)$ and $u_i^{APP}(t)$ are the power and the binary variable indicating the switching on or off of the device respectively.L_i and U_i are the hours in which the user defined the interval where he prefers the operation of his appliances. Furthermore, $\mathcal{A}_{non}$ correspond to the set of non-interruptible appliances.

Consumed power: As a counterpart to the previous restriction, it must be ensured that the power consumed by these devices must be their nominal power for their correct operation, on the other hand, it must also be established that the power consumed is the nominal power only if the appliance is turned on during the simulated hour, also including the variable u_i^{APP}.

$$P_i^{APP}(t) = u_i^{APP}(t) \cdot P_{R,i}^{APP}(t) \qquad \forall t \in \mathcal{T} \qquad \forall i \in \mathcal{A}_{non} \tag{3.6}$$

Where $P_{R,i}$ is the rated power of the appliance i.

Guarantee of non-interruptibility: In addition to the power restrictions, it must be ensured that the device does not divide its operation into different time slots, thus guaranteeing its non-interruptibility.

$$\sum_{t=j}^{j+T_{L,i}-1} u_i^{APP}(t) \geq T_{L,i} \cdot (u_i^{APP}(j) - u_i^{APP}(j-1)) \quad \forall j \in (L_i, U_i - T_{L,i} + 1] \quad \forall i \in \mathcal{A}_{non} \tag{3.7}$$

Where $T_{L,i}$ is the required device power-on duration of the appliance i.

If j is such that the device remains in the same previous state (if it was off and remains off, or if it was on and remains on) the restriction is deactivated because the sum must be greater than or equal to zero. In the case that j is such that it is the instant in which the equipment is turned on, the restriction is activated and the sum of intervals in which the appliance is turned on must be greater or equal to $T_{L,i}$, thus ensuring that once it is turned on it cannot be turned off in between the interval, because if that happens the sum is less than $T_{L,i}$.

It is important to note that the use of the greater or equal operator is to be able to deactivate the restriction. The power-on time of each appliance is minimized by the other constraints.

Power-on time: The switch-on of the non-interruptible appliance must coincide with its previously defined duration. This is achieved through the variable u_i^{APP}.

$$\sum_{t=L_i}^{U_i} u_i^{APP}(t) = T_{L,i} \qquad \forall i \in \mathcal{A}_{non} \tag{3.8}$$

User satisfaction: To determine the user dissatisfaction, the model proposes equation 3.9, where considering that equation 3.8 minimizes the turn-on time, the minimization of ζ_i makes the time slots as small as possible, and the appliance task is completed as soon as possible, being this favorable for the user.

$$\zeta_i = \sum_{t=L_i}^{U_i} (1 + \epsilon_i \cdot t) \cdot u_i^{APP}(t) \qquad \forall i \in \mathcal{A}_{non} \tag{3.9}$$

Where ϵ_i is a coefficient that indicates the importance given by the user to the appliance i.

3.1.1.2. Interruptible Appliances Restrictions

The following are the restrictions of appliances whose energy consumption can be divided into one or more time slots, providing greater flexibility compared to non-interruptible appliances.

Devices turned off when out of time range: When the time does not coincide with the user-defined intervals, the appliances cannot operate, so their power must be zero.

$$P_i^{APP}(t) = 0 \qquad \forall t \notin [L_i, U_i] \qquad \forall i \in \mathcal{A}_{in} \tag{3.10}$$

Required energy: Although this type of appliance may divide its consumption into different time slots, it must be satisfied that it receives the required amount of energy during the time in which demand management is performed.

$$\sum_{t=L_i}^{U_i} P_i^{APP}(t) \geq E_i^{APP} \qquad \forall t \in \mathcal{T} \qquad \forall i \in \mathcal{A}_{in} \tag{3.11}$$

It is important to note that although the comparison is between energy and power, the term on the left represents energy since a time step of one hour is implicit in each index of the summation.

Power consumption: It must be ensured that the power ranges in which the appliance operates must be within the allowed ranges, in addition to being consistent with the hours in which the variable $u_i(t)$ indicates whether it is on or off.

$$0 \leq P_i^{APP}(t) \leq P_{R,i}^{APP}(t) \qquad \forall t \in \mathcal{T} \qquad \forall i \in \mathcal{A}_{in} \tag{3.12}$$

User satisfaction: User satisfaction for this type of appliance is analogous to the case of non-interruptible appliances.

$$\zeta_i = \sum_{t=L_i}^{U_i} (1 + \epsilon_i \cdot t) \cdot u_i^{APP}(t) \qquad \forall i \in \mathcal{A}_{in} \tag{3.13}$$

3.1.1.3. Thermostatically Controlled Appliances Restrictions

For demand management, thermostatically controlled appliances such as air conditioners are also considered. The particularity of these appliances is that their operation is not delimited by a range of hours, as they operate continuously and depend on environmental factors and/or previous states of the device itself.

For this type of consumption, two types of appliances are considered: Air Conditioning and Water Heater. Since the behavior of both is different, it is necessary to differentiate them on the basis of the constraints to which each appliance must respond, generating two new subsets of appliances:

$$\{AC, WH\} \in \mathcal{A}_{ther} \tag{3.14}$$

Nominal Power: From the setpoint that is wanted to be established in the temperature, the appliance must consume a certain level of power, which must not exceed the nominal value.

$$0 \leq P_i^{APP}(t) \leq P_{R,i}^{APP}(t) \qquad \forall t \in \mathcal{T} \qquad \forall i \in \mathcal{A}_{ther} \tag{3.15}$$

Temperature limits: These types of appliances operate by adjusting the temperature setpoint, where in addition to the technical limits, the limits set by the user must be considered. Therefore, a restriction must be defined to ensure that the temperature of these appliances must not exceed the limits set by the users.

$$\theta_i^{dn} \leq T_{u,i}(t) \leq \theta_i^{up} \qquad \forall t \in \mathcal{T} \qquad \forall i \in \mathcal{A}_{ther} \tag{3.16}$$

In the equation 3.16 θ_i^{dn} and θ_i^{up} are the lower and upper temperature limits respectively.

Temperature control: Since the objective of these appliances is to maintain the temperature in a range defined by the user as close as possible to the ideal temperature, it is necessary to establish as restrictions the equations that link the power consumed with the temperature obtained. In addition to the above, physical constraints are also included based on the behavior of the different thermostatically controlled appliances.

- **Air Conditioning**

$$T_{u,i}(t) = T_{u,i}(t-1) + \eta \cdot (W_{out}(t) - T_{u,i}(t-1)) + \gamma \cdot P_i^{APP}(t) \; \forall t \geq 1 \; \forall t \in \mathcal{T} \; \forall i \in AC \tag{3.17}$$

Where $T_{u,i}(t)$ is the temperature of the user's appliance i at time t, W_{out} is the outdoor temperature, and η and γ are coefficients representing the thermal conditions of the environment in which the Air Conditioning is located.

The above constraint describes the evolution of the temperature inside the residence from the power consumed by the AC, where this also depends on the outdoor temperature, where a greater difference of the outdoor temperature with respect to the temperature perceived by the user in the previous period means a higher power consumption, as it must adjust a larger temperature gap.

- **Water Heater**

$$\sum_{k=1}^{t} P_i^{APP}(k) \geq \sum_{k=1}^{t} \rho_{wh}(t) \qquad \forall t \in \mathcal{T} \qquad \forall i \in WH \tag{3.18}$$

Where ρ_{wh} is the hot water demand. It is important to note that while the term on the left considers power, physically this constraint is tied to energy and how much is needed as a function of water demand. Implicit in this term is a one-hour step, which transforms the term units of the summation to energy. This restriction establishes that the energy consumed must be such that the hot water demand can be supplied.

$$\rho_{wh}(t) = \lambda \cdot m(t) \cdot c_w \cdot (T_{u,i}(t) - T_{cold}) \qquad \forall t \in \mathcal{T} \qquad \forall i \in WH \tag{3.19}$$

The constraint 3.19 defines how the demand for hot water is linked to the user's perceived temperature, where $m(t)$ is the mass of water in period t, c_w is the specific heat of water, λ is a constant for unit conversion and T_{cold} is the temperature of inlet cold water.

$$\sum_{k=1}^{t} P_i^{APP}(k) \leq \lambda \cdot M \cdot c_w \cdot (T_{u,i}(t) - T_{cold}) + \sum_{k=1}^{t} \rho_{wh}(t) \qquad \forall t \in \mathcal{T} \qquad \forall i \in WH \tag{3.20}$$

Constraint 3.20 states that the heat storage in each time slot must not exceed the water storage limit, limited by M which corresponds to the mass of water in full storage.

User satisfaction: Unlike the other types of appliances, in this case user satisfaction is determined by how far the temperature is from the user's preferred value.

To model the satisfaction associated with the temperature, weights of each of the temperature limits chosen by the user must be defined, so that through the modification of these values the temperature setpoint in each time slot can be defined. In this way the weights $w_{1,i}$, $w_{2,i}$ and $w_{3,i}$ are defined by the optimization, where the sum of the three must be 1, and $w_{1,i}$ and/or $w_{3,i}$, which correspond to the weights of the lower and upper limit temperatures respectively, must be 0.

The aforementioned translates into restrictions described in equations 3.21 through 3.25.

$$w_{1,i}(t) \leq z_{1,i}(t), \quad w_{2,i}(t) \leq z_{1,i}(t) + z_{2,i}(t), \quad w_{3,i}(t) \leq z_{2,i}(t) \quad \forall t \in \mathcal{T} \tag{3.21}$$

$$w_{1,i}(t) + w_{2,i}(t) + w_{3,i}(t) = 1 \quad w_{k,i}(t) \geq 0 \quad \forall k = 1,2,3 \quad \forall t \in \mathcal{T} \tag{3.22}$$

$$z_{1,i}(t) + z_{2,i}(t) = 1 \quad z_{k,i}(t) = 0 \; or \; 1 \quad \forall k = 1,2 \quad \forall t \in \mathcal{T} \tag{3.23}$$

$$T_{u,i}(t) = \theta_i^{dn} \cdot w_{1,i} + T_{c,i} \cdot w_{2,i} + \theta_i^{up} \cdot w_{3,i} \qquad \forall t \in \mathcal{T} \qquad \forall i \in \mathcal{A}_{ther} \tag{3.24}$$

$$\zeta_i = w_{1,i} \cdot \epsilon_i + w_{3,i} \cdot \epsilon_i \qquad \forall i \in \mathcal{A}_{ther} \tag{3.25}$$

Where θ_i^{dn} and θ_i^{up} are the lower and upper limits of temperature desired by the user.

3.1.1.4. Energy Storage System Restrictions

In some of the users to be modeled there will be energy storage systems, so their restrictions must be considered, which correspond to both capacity limits and the flow of energy from or to the grid.

Discharge of the storage system: The power used or sold by the battery corresponds to the discharge of the battery, considering an efficiency η_{ESS}^d.

$$P_{ESS}^{used}(t) + P_{ESS}^{sold}(t) = \eta_{ESS}^d \cdot P_{ESS}^d(t) \qquad \forall t \in \mathcal{T} \tag{3.26}$$

Where P_{ESS}^{used}, P_{ESS}^{sold} and P_{ESS}^d are the used, sold and discharge power of the battery system respectively.

Charging rates: As with the appliances seen above, the batteries have a maximum power to operate without affecting the service life, and charge and discharge limits are defined for the storage system.

$$0 \leq P_{ESS}^c \leq R_{ESS}^c \cdot \mu_{ESS}(t) \qquad \forall t \in \mathcal{T} \tag{3.27}$$

$$0 \leq P_{ESS}^d \leq R_{ESS}^d \cdot (1 - \mu_{ESS}(t)) \qquad \forall t \in \mathcal{T} \tag{3.28}$$

Where $\mu_{ESS}(t)$ is a binary variable indicating the charge (1) or discharge (0) of the battery.

Evolution of the state of energy: Since the use of the battery considers a temporal coupling for its optimization, it is necessary to define a constraint to describe the evolution of the state of energy over time, and that it remains within its limits.

$$S_{ESS}(t) = S_{ESS}(t-1) + \eta_{ESS}^c \cdot P_{ESS}^c - \eta_{ESS}^d \cdot P_{ESS}^d \qquad \forall t \geq 1 \qquad \forall t \in \mathcal{T} \tag{3.29}$$

$$S_{ESS}(t) = S_{ESS}^{ini} \qquad if \quad t = 1 \tag{3.30}$$

$$S_{ESS}^{min} \leq S_{ESS}(t) \leq S_{ESS}^{max} \qquad \forall t \in \mathcal{T} \tag{3.31}$$

3.1.1.5. Photovoltaic Panels Restrictions

In addition to storage systems, the possibility of homes having photovoltaic panels is also considered, so a restriction on this technology is also included.

Use of photovoltaic generation: The power generated by the panels can be used for the household, either to charge the battery system or to supply the appliances.

$$P_{PV}^{use}(t) + P_{PV}^{sell}(t) = P_{PV}(t) \qquad \forall t \in \mathcal{T} \tag{3.32}$$

3.1.1.6. Power Flow Between the User and the Grid Restrictions

Once all the restrictions for the different elements present in the user's home have been defined, the interactions between the grid and the user must also be considered, which will ultimately generate a systemic impact when demand management is massive.

Power injected to the grid: Households with storage systems and/or solar panels have the possibility to sell energy to the grid when deemed convenient, so P_{sell} should be defined as:

$$P_{sell}^{PV} + P_{sell}^{ESS} = P_{sell} \qquad \forall t \in \mathcal{T} \tag{3.33}$$

Power Balance: It must be ensured that the power intended to supply consumption matches the power demanded by the different appliances and the storage system in each time slot. In this restriction, what was proposed in the original model was modified to include unmanageable devices.

$$P_{buy}(t) + P_{use}^{ESS}(t) + P_{use}^{PV}(t) = P_{ESS}^{c}(t) + P_{non-mana}(t) + \sum_{i \in \mathcal{A}} P_i^{APP}(t) \qquad \forall t \in \mathcal{T} \tag{3.34}$$

Where $P_{non-mana}$ is the non-manageable power of the household, which, despite not being controllable, should be considered within this constraint, since it indirectly affects the optimum. An example of this would be a high unmanageable consumption in an hour with high solar generation can considerably modify the power purchased from the grid in that hour.

Logic of power exchange: Since the formulation of the model gives rise to the purchase and sale of energy, it must be consistent with the fact that the flow of energy is in only one direction, i.e., energy cannot be bought and sold at the same time, for which the binary variable μ_{grid} is used to determine whether energy is being bought or sold, with the values 1 and 0 respectively.

$$P_{buy}(t) \leq N_1 \cdot \mu_{grid}(t) \qquad \forall t \in \mathcal{T} \tag{3.35}$$

$$P_{sell}(t) \leq N_2 \cdot (1 - \mu_{grid}(t)) \qquad \forall t \in \mathcal{T} \tag{3.36}$$

Where N_1 and N_2 are numbers large enough not to limit the power purchased and supplied.

3.1.2. Model output

Once all the restrictions and the objective function have been defined, it is possible to run the model to obtain the consumption profile of a user based on the importance he/she gives to his/her welfare. The first step is to build the user, which will be discussed in the following section, then the user's data are entered into the model and the main result is the daily consumption profile (or generation profile in case it is convenient and has photovoltaic generation or storage systems), as shown in Figure 3.2 as an example.

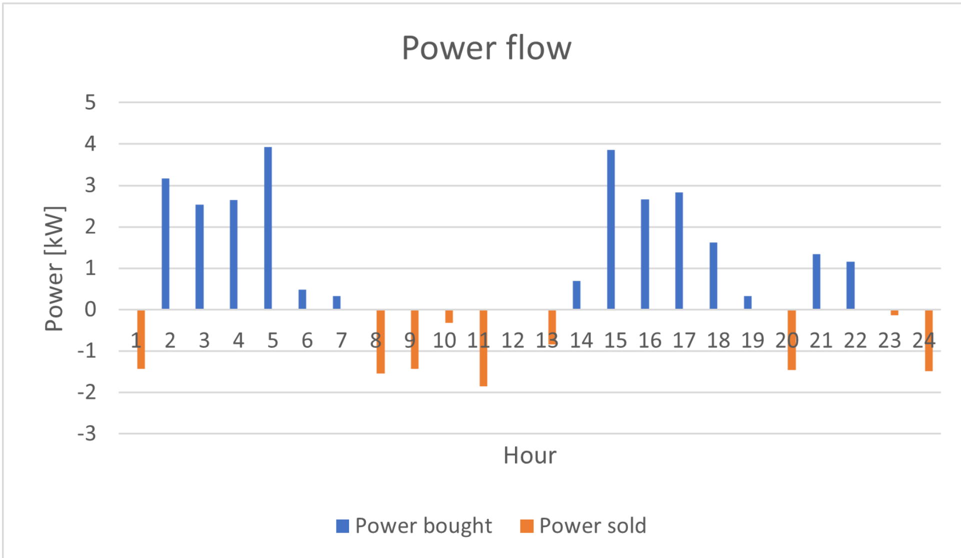


Figure 3.2: Example of consumption profile obtained.

On the other hand, this result can be disaggregated to obtain the consumption profile for the different types of appliance or for manageable and unmanageable appliances, as shown in figures 3.3 and 3.4 respectively.

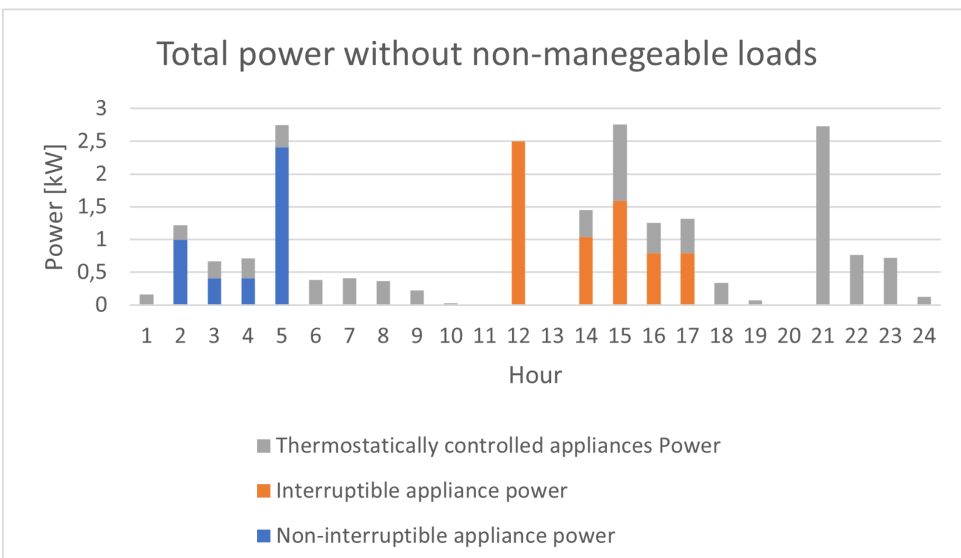


Figure 3.3: Example of appliances consumption profile obtained, disaggregated into manageable and non-manageable demand.

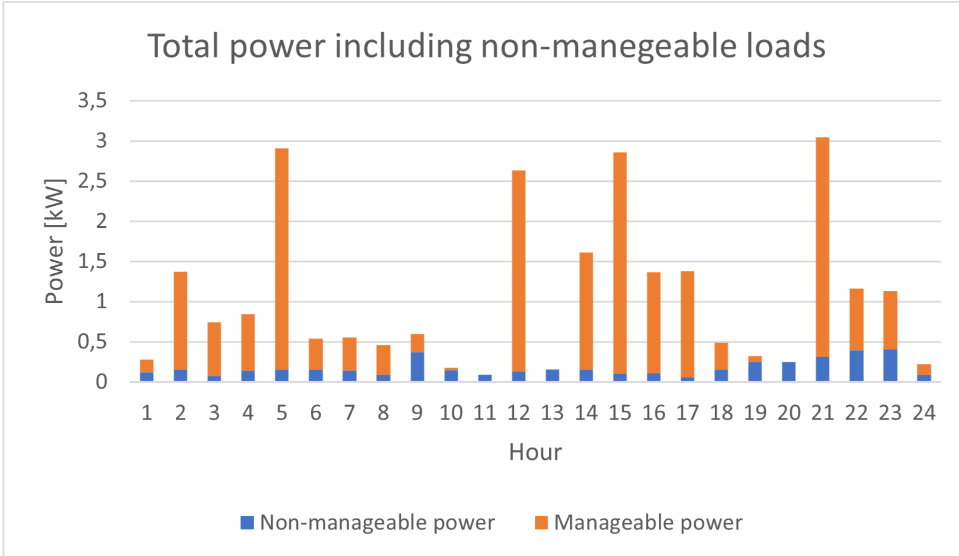


Figure 3.4: Example of appliances consumption profile obtained disaggregated into the diferents types of appliances.

It is also possible to obtain how the temperature setpoint of the thermostatically controlled appliance varies throughout the day, as shown in the examples in Figures 3.5 and 3.6 respectively.

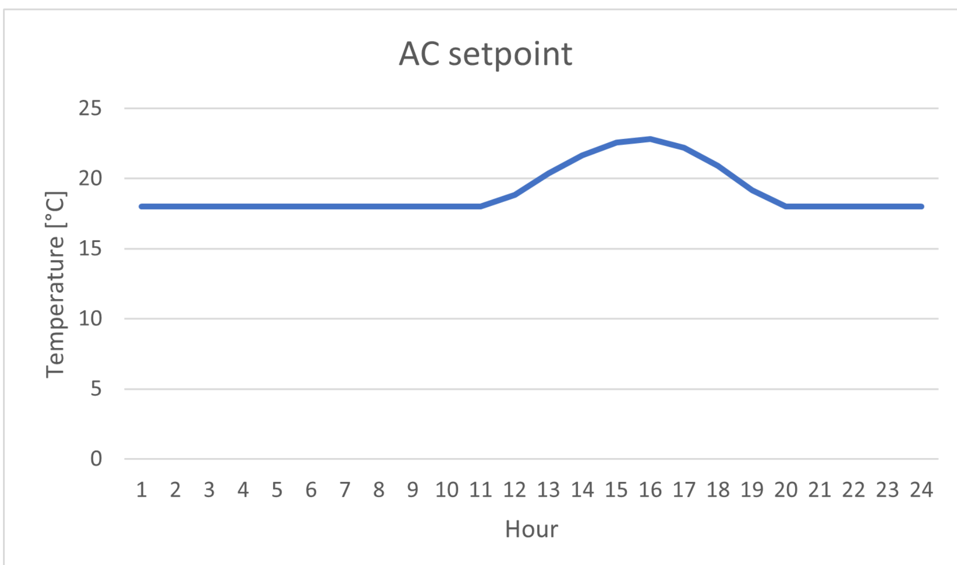


Figure 3.5: Example of AC setpoint along the day obtained from the model.

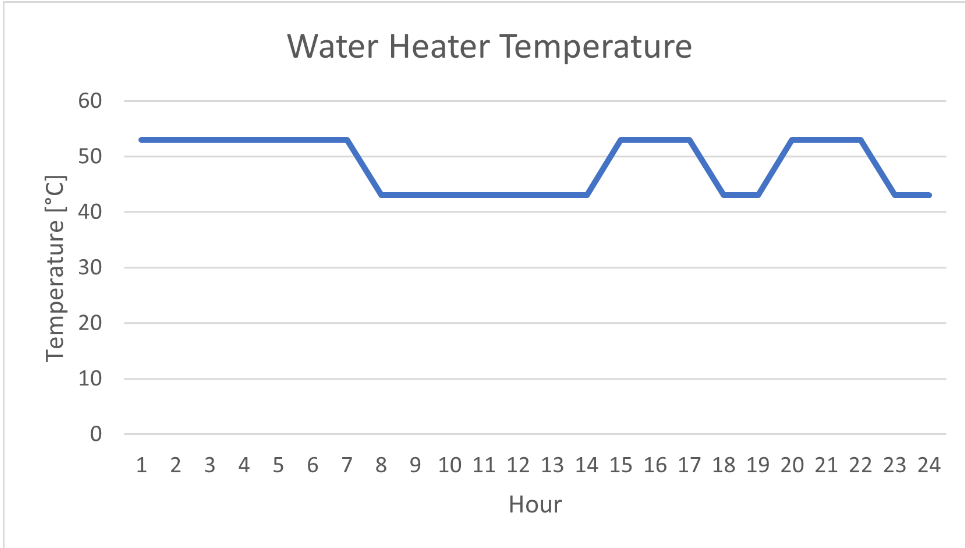


Figure 3.6: Example of WH setpoint along the day obtained from the model.

3.1.3. Creation of grid users

In order to carry out the experiments to analyze the impact of non-compliance with demand side management, more than one user must be available, so a method must also be determined for the creation of the users that will participate in the system, defining their appliances, preferences and distributed resources.

3.1.3.1. Generation of appliances

The first step for the creation of users is to define the list of appliances, and thus the unmanageable demand. This is done using the high-resolution stochastic integrated thermal-electrical domestic demand model [7], which allows obtaining the consumption curve of a randomly generated user based on the probability of the presence of appliances, the probability of their use and their associated times of use. Figure 3.1 shows an example of the random creation of a user's appliances list.

Table 3.1: Example of user appliances generation.

Appliance	**Present in user dwelling**
Chest freezer	FALSE
Fridge freezer	TRUE
Refrigerator	TRUE
Upright freezer	FALSE
Answer machine	TRUE
Cassette / CD Player	FALSE
Clock	FALSE
Cordless telephone	TRUE
Hi-Fi	TRUE
Iron	TRUE
Vacuum	TRUE
Fax	FALSE
Personal computer	TRUE
Printer	FALSE
TV 1	TRUE
TV 2	FALSE
TV 3	FALSE
VCR / DVD	TRUE
TV Receiver box	TRUE
Hob	TRUE
Oven	FALSE
Microwave	FALSE
Kettle	TRUE
Small cooking (group)	TRUE
Dish washer	FALSE
Tumble dryer	FALSE
Washing machine	TRUE
Washer dryer	FALSE
WH (all WH appliances)	TRUE
EV	FALSE
PP	TRUE
AC	FALSE

Once the user list of appliances has been generated, it is possible to disaggregate it in order to separate the unmanageable demand, thus obtaining the value of $P_{non-mana}$ for the period being worked on, as illustrated in Figure 3.7.

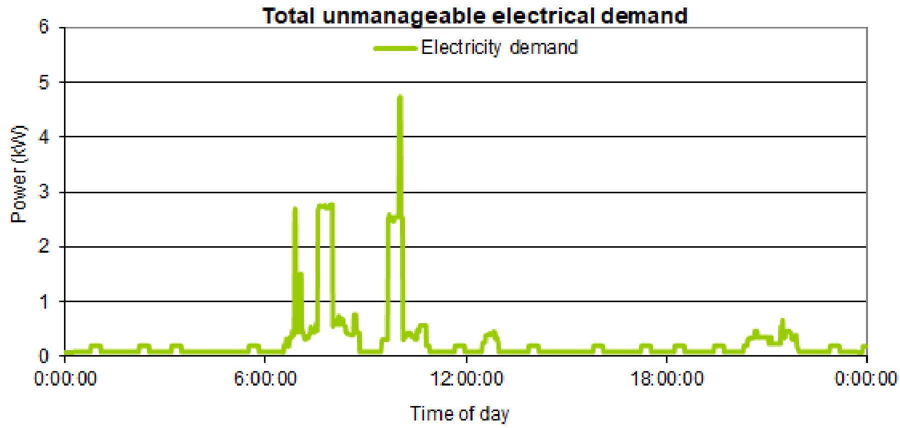


Figure 3.7: Example of generated unmanageable demand curve.

On the other hand, if there is a water heater in the appliances, a random water demand profile is also generated, which is used as input for the model when determining the water heater consumption, as illustrated by way of example in figure 3.8.

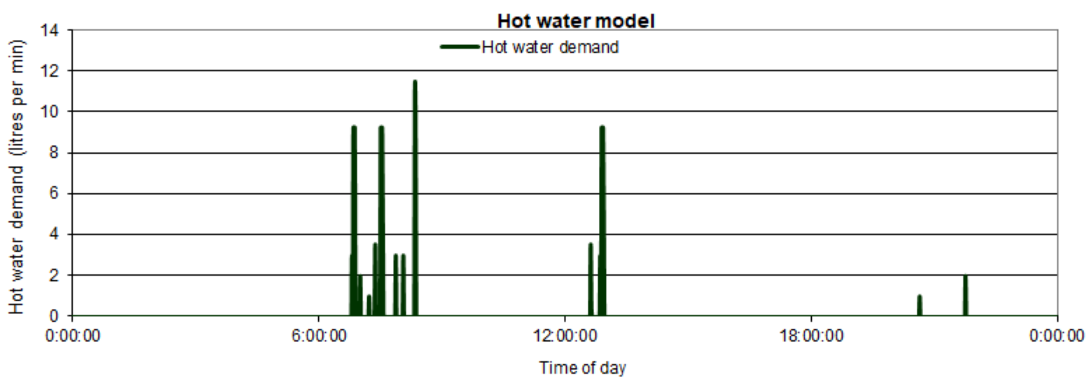


Figure 3.8: Example of generated hot water demand curve.

3.1.3.2. User preferences

In addition to the list of devices, it is important to define the relevance given by the user to each appliance, the ranges in which he allows them to operate, and the thermostatically controlled devices preferences, which are randomly generated based on the values used in [6]. An example of this with some appliances is ilustrated in table 3.2.

Table 3.2: Example of generated user preferences.

Appliance	Duration	Lower limit	Upper limit	Rated power [kW]	Resentment coefficient
Iron	1	12	14	1.0	0.3
Vacuum	1	15	18	2.0	0.4
Dish washer	5	8	18	1.1	0.1
Washing machine	3	3	15	0.4	0.2

3.1.3.3. Distributed Energy Resources

As with appliances, the presence of elements such as solar panels, storage systems and electric vehicles must be defined. For the particular case of these three elements it is not convenient to determine their presence randomly from statistics, because currently the presence of these elements is very low, so that if probabilities were used it is very unlikely to obtain any user who owns any of these elements. For the same reason, the work is done in a hypothetical scenario in which, in addition to the implementation of demand side management at residential level in the system, there is a greater presence of distributed energy resources, so that, although they will not be present in all residences, there is a greater probability of having some of these elements, imposing their presence manually with this consideration.

3.1.3.4. User creation output

Once the list of appliances and the parameters associated to each one of them have been defined, sufficient information is available to execute the demand management model. For this purpose, the list of appliances and their respective information is recorded in an Excel spreadsheet, which is subsequently exported to the FICO software where the different numerical values are assigned to their respective variables.

3.2. Description of the electric system model

For the experiments to be carried out in the study of this thesis it is necessary to see the impact on an electrical system, so an economic dispatch model must also be implemented, where the impacts of changes in user behavior can be seen. For this purpose, a simple dispatcher is developed, which, based on the different demand profiles promised, operates the system for 24 hours and calculates the cost of operation in the event that users comply with what is promised and in the event that they do not comply. Depending on the scenario being carried out, the percentage of users that will not comply with the demand management program is determined, where this percentage of users divert their consumption based on the non-compliance simulation.

The dispatcher considers the time horizon exposed in the scope of the thesis. This scope considers a time horizon of 24 hours, mainly because this is the time horizon considered by the demand management model used. Operating the system in a time longer than 24 hours would be inconsistent with the implemented demand management. This inconsistency is not theoretical but practical. What the model, and Enerdis, is looking for is for the user to provide information on his consumption daily. If they were asked for information for longer time horizons, they would not be able to give a reliable response due to the uncertainty of what their consumption would be like in, for example, one more week.

Based on the time horizon used, it is decided to limit the scope and complexity of the dispatcher used. A dispatcher similar to those proposed in [8] and [9] is built, where ramp restrictions and minimum on or off times are not considered.

3.2.1. Objective function and constraints

For the construction of the dispatcher, an optimization problem is posed for three types of units: generation, loads and transmission equipment [44]. The objective of this optimization problem is the minimization of system operating costs from the cost functions of the generating units present.

Once the cost function has been defined, the constraints of this problem must also be considered, which include generation and transmission limits, power balance and Kirchoff's law. It is important to note that the problem does not consider Ohmic losses.

The objective function is:

$$min \sum_{t=1}^{24}\sum_{i=1}^{ng} C_i(P_i(t)) \tag{3.37}$$

Where C_i is the cost function of the i-th generator, ng is the number of generators present in the system, $P_i(t)$ is the power generated by the i-th unit in hour t, where a horizon of twenty-four hours is considered from what is established in the users consumption management model.

3.2.1.1. Generating unit restrictions

On and off of the machines: Binary variables must be defined to indicate the status of the generators.

$$u_i(t) = 0 \vee u_i(t) = 1 \qquad \forall t \in \mathcal{T} \tag{3.38}$$

Where $u_i(t)$ is the binary variable indicating whether the i-th generator is on (1) or off (0).

Generation limits: On the other hand, since the machines have maximum and minimum power ratings, restrictions must be established to guarantee operation within the established margins considering the status of the machines.

$$P_{i_{min}} \cdot u_i(t) \leq P_i(t) \leq P_{i_{max}} \cdot u_i(t) \qquad \forall t \in \mathcal{T} \tag{3.39}$$

Where $P_{i_{min}}$ is the minimum power of generator i and $P_{i_{max}}$ is the maximum power of generator i.

3.2.1.2. Power system restrictions

Energy balance: In order to supply the system's electricity demand, a balance between generation and demand must be defined, so that in every hour of the analyzed horizon the energy demanded and generated have to be the same.

$$\sum_{i \in ng \mid bus(g)=b} P_i(t) + \sum_{l \in nl \mid to(l)=b} f_l(t) = D_{b_{expected}}(t) + \sum_{l \in nl \mid from(l)=b} f_l(t) \forall b \in \mathcal{B} \forall t \in \mathcal{T} \tag{3.40}$$

Equation 3.40 establishes that for each bus of the system it must be fulfilled that the power generation occurring in it, together with the flow it receives from other buses, must be equal to the demand in the bus plus the power exported to other buses of the system.

In equation 3.40 $bus(g)$ indicates the bus to which the generator g is connected. On the other hand, nl is the number of lines present in the system, and the functions $to(l)$ and $from(l)$ indicate the destination and origin bus of the flow $f_l(t)$ respectively. Finally, $D_{b_{expected}}(t)$ indicates the demand for bus b in hour t.

Flow limits: Since transmission lines do not have infinite capacity, the optimization problem must limit the capacity of the lines based on the system information.

$$-f_{max}(l) \leq f_l(t) \leq f_{max}(l) \;\; \forall l \in \mathcal{L} \;\; \forall t \in \mathcal{T} \tag{3.41}$$

Where $f_{max}(l)$ is the capacity of line l.

Kirchoff's Law: The system in which the work is being done is represented by a circuit built from nodes and transmission lines that connect them with certain reactance. The power flow equations must be respected considering the angular coupling between buses, for this the DC power flow equation is used.

$$f_l(t) = \frac{\theta_{from(l)}(t) - \theta_{to(l)}(t)}{x_l} \;\; \forall l \in \mathcal{L} \;\; \forall t \in \mathcal{T} \tag{3.42}$$

Where $\theta_{from(l)}(t)$ corresponds to the origin bar angle of the flow through line l, $\theta_{to(l)}(t)$ to the destination bar angle of the flow of line l and x_l is the reactance of line l.

3.2.1.3. Operation of the system

Once the dispatch has been made, the system is operated in real time during the day. The solution of the operation of the system is expected to be the same obtained from the previous optimization problem. But in the scenarios where the demand differs from the expected one due to non-compliance, it is necessary to include emergency generation for cases in which the demand cannot be supplied from the operation defined due to non-compliance. Considering the above, the optimization problem for the operation is as follows:

$$min \;\; \sum_{t=1}^{24}\sum_{i=1}^{ng} C_i(P_i(t)) + \sum_{t=1}^{24}\sum_{b=1}^{nb} C_{emergency}(P_{loss_b}(t)) \tag{3.43}$$

Where $C_{emergency}$ is the cost function of the emergency generation, $P_{loss_b}(t)$ is the power that cannot be supplied in hour t in bus b from the operation defined and nb is the number of buses present in the system. It is important to note that in the event that the emergency generation is not sufficient to supply the remaining power, VoLL must be incurred, which would imply a considerable increase in operating costs. For the purposes of this study, VoLL is not considered since it is assumed that the emergency generators can always meet the power difference, so the increase in costs for the energy not supplied will be less or equal to a case in which VoLL is considered.

The rest of the restrictions are analogous to those described above, except for the balance restriction. The power that cannot be supplied must now be included and the real demand is considered instead of the expected one:

$$\sum_{i\in ng \mid bus(g)=b} P_i(t) + \sum_{l\in nl \mid to(l)=b} f_l(t) + P_{loss_b}(t) = D_{b_{real}}(t) + \sum_{l\in nl \mid from(l)=b} f_l(t)$$
$$\forall b \in \mathcal{B}\ \forall t \in \mathcal{T} \tag{3.44}$$

Where $D_{b_{real}}(t)$ is the real demand of bus b in hour t. With this change in the constraint, the system is operated based on the real demand using FICO and the real operating cost of the system given a certain expected demand curve is obtained. From this it is possible to determine the impact of non-compliance by users, being possible to quantify it from the variation in costs and the amount of energy supplied with emergency generation.

3.2.2. Cost functions

For the construction of the cost functions, the information available in the scheduled operation of the national electricity coordinator [60] is used and the data of multiple real machines of the system in November 2017 were extracted. Then, as in [61] they are varied to obtain the set of machines to be used with values similar to the real ones, but giving rise to a hypothetical system. The way to obtain the technical minimums is also analogous to [61], where machines with technical maximums similar to those previously used are searched in the information offered by the national electricity coordinator [62], and based on these generators the technical minimums are defined.

On the other hand, the cost of the emergency generator to be used for the operation of the system must be defined. It was defined from the information available in the technical report of the SEN and SSMM Short and Long Duration Failure Cost Study [63], which provides values for emergency generators.

The renewable generation present in the system corresponds to solar energy and is attributed a zero cost, since the operating and maintenance costs are disregarded, and its fuel and non-fuel variable costs are zero [64].

3.2.3. Model Output

The outputs of this model is the power of each generator of the system for each hour of the day, which also allows obtaining the operating cost of the system. The results of this model allow analyzing the impact of non-compliance by contrasting different system operating costs based on expected demand and real demand, in addition to providing information on the use of the emergency generator, which in some systems could lead to loss of load.

From the output of the model it is possible to compare the costs and the energy supplied by the emergency generator. Table 3.3 shows an example where the cases of real demand and expected demand are compared when 24 % of the network users are managed.

Table 3.3: Example of a comparison between real and expected demand cases.

Scenario	Manageable users	Users with non-compliance	Non-compliance band	Expected cost [$]	Real cost [$]	Emergency Generator [MWh]
37	6/25	0/25	0 %	408,067.925	408,067.925	0
38	6/25	1/25	25 %	408,067.925	410,054.193	16.7546505
39	6/25	2/25	25 %	408,067.925	411,702.933	19.5967557
40	6/25	3/25	25 %	408,067.925	408,465.525	8.37580456
41	6/25	4/25	25 %	408,067.925	408,171.24	8.37580456
42	6/25	5/25	25 %	408,067.925	408,117.797	8.37580456
43	6/25	6/25	25 %	408,067.925	410,598.632	14.635783
44	6/25	1/25	50 %	408,067.925	410,831.773	15.7546505
45	6/25	2/25	50 %	408,067.925	415,268.444	31.8943414
46	6/25	3/25	50 %	408,067.925	416,162.053	40.3778385
47	6/25	4/25	50 %	408,067.925	415,390.48	39.3431232
48	6/25	5/25	50 %	408,067.925	414,924.675	39.3431232
49	6/25	6/25	50 %	408,067.925	416,989.082	43.6031016

3.3. Non-compliance simulation

In order to model the non-compliance with the demand management program, two new values of the parameter ω_2 are defined for each user to simulate the deviation of the user when the importance given to his welfare is modified, if this occurs, the user's consumption curve is affected.

In order to obtain the new values of ω_2 from the user, a random number "n" between 0 and 1 is generated, then it is defined if the deviation "d" will be such that ω_2 increases or decreases. With these values it is now possible to determine the new ω_2 for different deviation bands "b".For the purposes of this study bands of 25 % and 50 % deviation were used (low and high consumption deviation). The 25 % band was used to guarantee that every user actually changes his demand profile (details in appendix B), and the band of 50 % was used to have variations in welfare of the same magnitude as those used by the demand management model used.

The way to obtain the new values of ω_2 is:

$$\omega_2' = \omega_2 + d \cdot (n \cdot b) \tag{3.45}$$

By generating a random number and direction of deviation per user, it is possible to simulate non-compliance at the systemic level.

3.4. Combination of models

To obtain results, all the models and procedures described in this chapter, illustrated in the block diagram in figure 3.9, must be combined. The procedure of the diagram shown is:

1. Creation of users: From the CREST model, the models of the different types of users that will be present in the network are created. Defining the appliances they have, the preferences of each one of them and the presence of storage systems or solar generation. Each user model represents a certain number of users of the network, being this a simplification that allows working with orders of magnitude of consumption comparable to those of the generation of the machines present in the system.

2. Creation of demand profiles: Once the users have been created, the demand management model is used to determine the different demand profiles to be considered by the system based on price signals, ambient temperature and solar generation.

3. Economic dispatch: Once the expected demand is known, the economic dispatch is carried out.

4. Define the real demand of the system: Based on the non-compliance simulation, the users that will not meet the expected demand are determined and their real demand curve is calculated.

5. Operation based on real and expected demand: The operation of the system is made based on the expected demand. After that, the system is operated considering the real demand of the system. At this point the difference in costs is obtained by comparing the cases with and without non-compliance, in addition to the amount of energy not supplied.

6. Sensitivity analysis: To study the impact of different levels of non-compliance, steps 4 and 5 are repeated for different non-compliance scenarios.

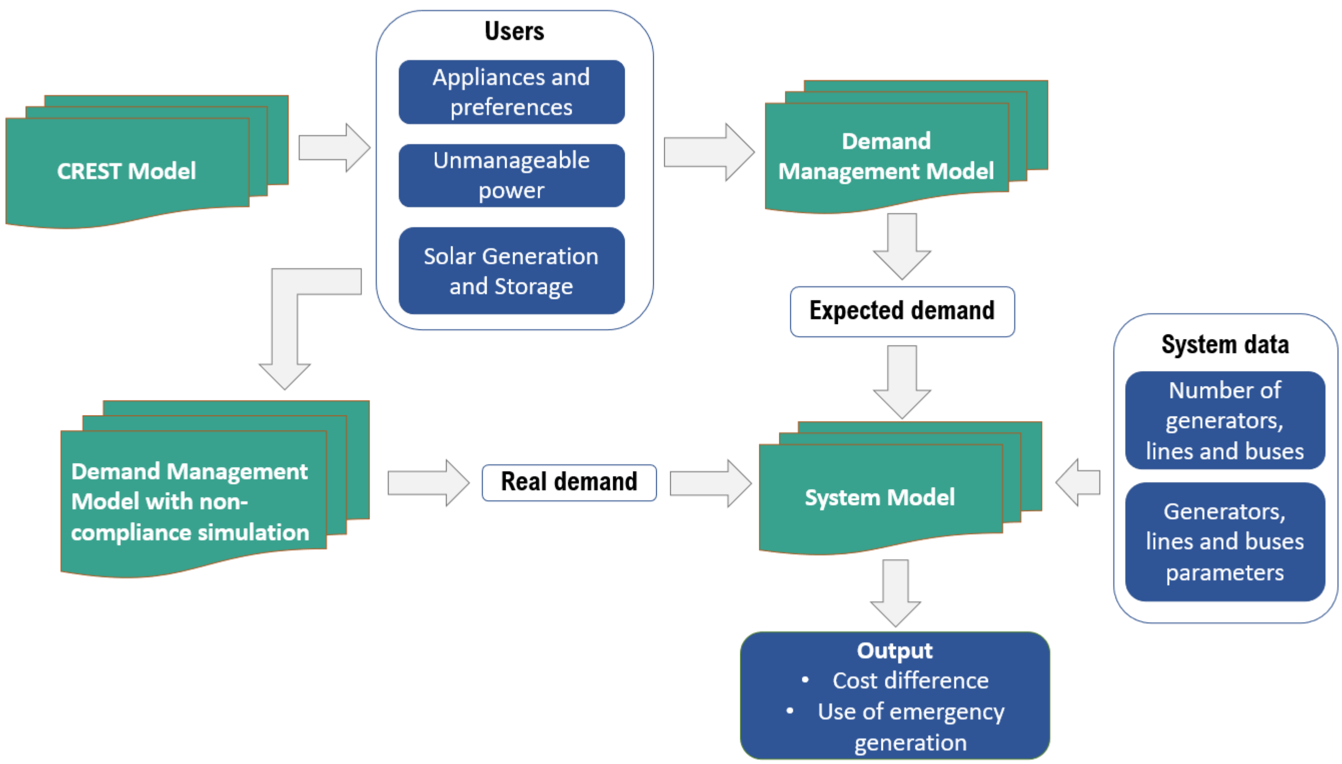


Figure 3.9: Model combination block diagram.

3.5. Computational Tools

For the construction of the models to be used for the demand management and economic dispatch, in addition to the management of results, it was necessary to use software that would facilitate the performance of these tasks, which mainly consist of solving mixed integer linear optimization problems (MILP), and data processing.

3.5.1. FICO Xpress

FICO Xpress software is used to build the demand management and economic dispatch models. This software is a tool that allows the resolution of highly complex optimization problems quickly through a programming language named *Mosel*. This software is used mainly for system modeling, and part of the problems it can solve are MILPs, being a good tool for the experiments that are carried out. It is important to note that FICO Xpress is capable of reading and writing Excel files, allowing the combined use of both software.

3.5.2. Excel

The use of Excel for the performed experiments is to record the results obtained from FICO Xpress and provide this software with the parameters it needs to simulate. Once the models are implemented, the parameters necessary for their use are imported from Excel, then, once the optimization has been carried out, the results and decision variables of interest are written to an Excel file.

3.6. Data Collection

For the correct operation of the model it is necessary to have the necessary inputs and parameters to solve the optimization problem. The data needed for the model are: Ambient temperature, solar and wind generation, price signals, the devices present in the user's dwelling, and as a result of the latter, its unmanageable demand.

For ambient temperature and generation, the solar explorer is used, where detailed information on solar generation is generated from a given location [65]. In addition, the wind generation was obtained from the wind explorer, whose operation is similar to that of the solar explorer [66].

The price signals were created from the national electricity coordinator information, which provides information on marginal costs in the different sectors of the system [67]. With that reference information and the system information, the price signal that the model uses for both the purchase and sale of energy was obtained.

To determine the user devices being simulated, the high-resolution stochastic integrated thermal-electrical domestic demand model provided by CREST [7] is used. From this model it is possible to determine which appliances were considered when simulating the user's consumption curve. Based on this and on what is indicated in [68], it is possible to determine which appliances will be manageable and thus filter the consumption so as to obtain a non-manageable consumption curve.

Chapter 4

Case study

This chapter presents case studies in which the impact of non-compliance with demand-side management programs is analyzed. In order to carry out these studies, the aforementioned methodology is applied to two different electrical systems.

First, a small electrical system is analyzed to make a preliminary analysis of the impact that non-compliance can generate, in order to determine whether a study in a more complex system is justified. The second case study is in a twenty-four bus system, where it is possible to make a deeper analysis of the impact of non-compliance. This because in this system it is possible to analyze a larger number of scenarios and work on a more complex system.

In addition to presenting the case studies, this chapter also shows the results. This results were obtained for each case study for different non-compliance scenarios based on the sensitivity analysis. For each scenario studied, the operating costs of the system and the use of emergency generators were obtained.

4.1. Four buses system

4.1.1. System description

In the first case study, the system shown in figure 4.1 was implemented. This system consist of four generators and four buses with one demand on each. Each demand represents a group of grid users. On the other hand, the technologies of the generators created for this system were Diesel, Carbon, LNG, and solar.

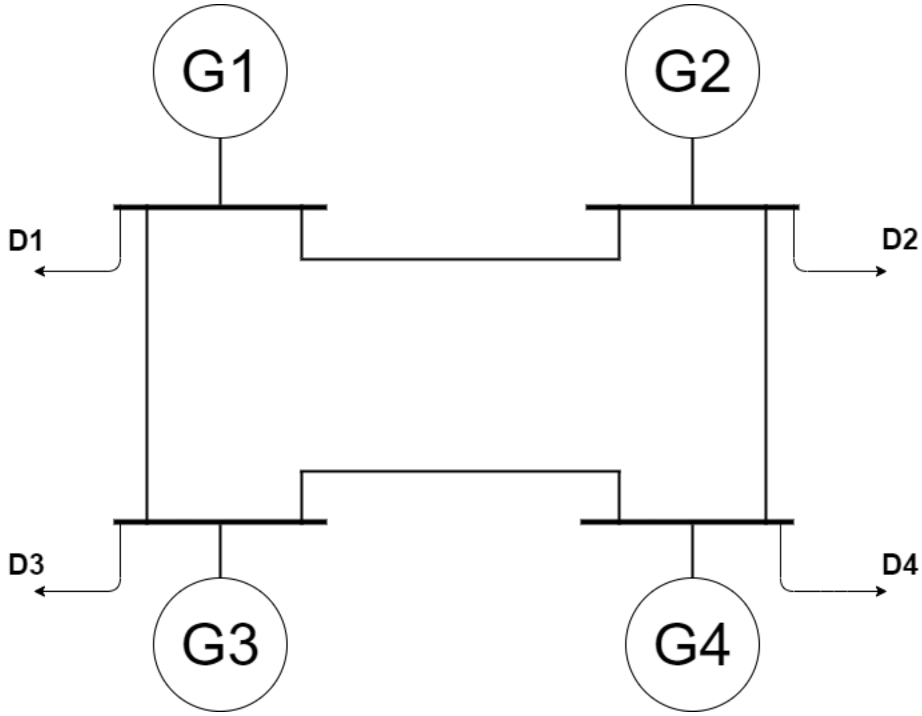


Figure 4.1: Four buses system.

For the simulation six standard users were created, where the manageable ones are up to five. In order to have consumption levels comparable to those of generation, each standard user represents ten thousand users in the grid. These were created as set out in the section 3.1.3 and the values of the parameter ω_2 for each manageable user are shown in the 4.1 table.

Table 4.1: ω_2 values for four buses system.

User type	original ω_2	new ω_2 [-25 %,25 %]	new ω_2 [-50 %,50 %]
1	0.5	0.71	0.93
2	0.5	0.58	0.67
3	0.7	0.51	0.32
4	0.3	0.45	0.6
5	0.5	0.69	0.87

Having defined the system, the users and the values of ω_2, it's only needed to define the solar generation, ambient temperature and price signal to have all the necessary information to perform the simulations of the hypothetical system created. The solar generation profile and ambient temperature were created with the help of information from the solar explorer. These curves are shown in appendix C. On the other hand, the price signal is shown in Figure 4.2.

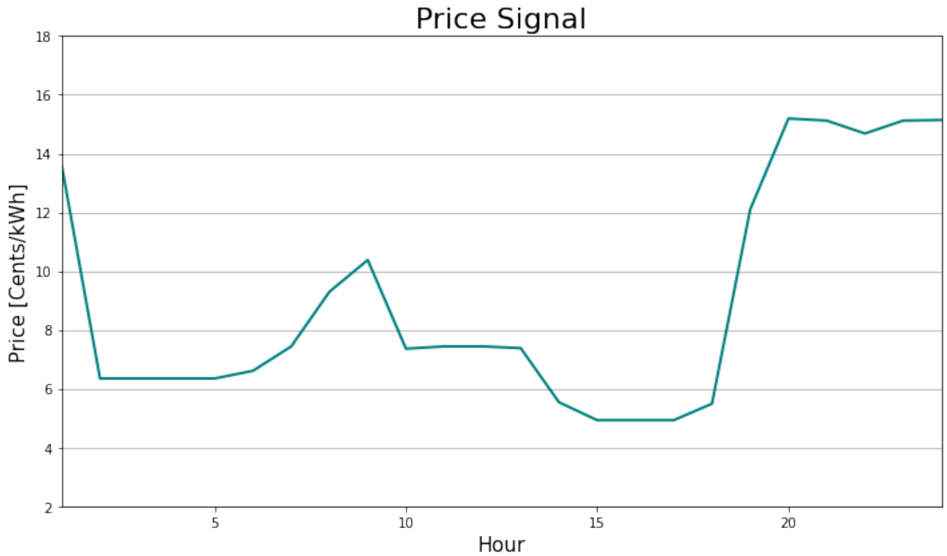


Figure 4.2: Four buses system price signal.

4.1.2. Sensitivity analysis

For the sensitivity analysis, three variables were modified as follows:

1. Number of manageable users.
2. Number of users in non-compliance with the demand management program.
3. Band of deviation of ω_2.

These adjustments in the system result in twenty-eight scenarios shown in Table 4.2. In each scenario at least one of the three variables mentioned above is modified. For each scenario an economic dispatch was performed to calculate the operating costs and the energy supplied by the emergency generation. Once the operating cost has been obtained, it is compared with a scenario in which there is no non-compliance.

Table 4.2: Four buses system scenarios.

Scenario	Manageable users	Users with non-compliance	ω_2 band
1	2/6	1/6	25 %
2	2/6	1/6	50 %
3	2/6	2/6	25 %
4	2/6	2/6	50 %
5	3/6	1/6	25 %
6	3/6	1/6	50 %
7	3/6	2/6	25 %
8	3/6	2/6	50 %
9	3/6	3/6	25 %
10	3/6	3/6	50 %
11	4/6	1/6	25 %
12	4/6	1/6	50 %
13	4/6	2/6	25 %
14	4/6	2/6	50 %
15	4/6	3/6	25 %
16	4/6	3/6	50 %
17	4/6	4/6	25 %
18	4/6	4/6	50 %
19	5/6	1/6	25 %
20	5/6	1/6	50 %
21	5/6	2/6	25 %
22	5/6	2/6	50 %
23	5/6	3/6	25 %
24	5/6	3/6	50 %
25	5/6	4/6	25 %
26	5/6	4/6	50 %
27	5/6	5/6	25 %
28	5/6	5/6	50 %

Once every scenario was simulated obtaining its operating costs, the totality of the results for this case study were obtained. Given the high number of scenarios, cost graphs are shown only for the scenarios with the most relevant results in figures 4.3, 4.4 and 4.5.

4.1.2.1. 50 % of manageable users

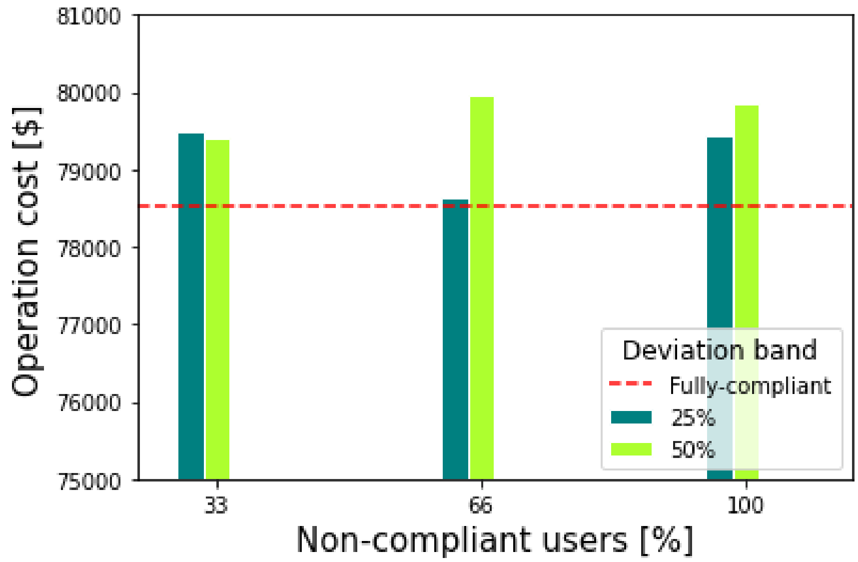


Figure 4.3: Four buses system, 50 % of manageable users: expected operation cost vs. real operation cost.

Figure 4.3 shows the different operating costs when 50 percent of the users of the four buses system are managed. From the graph it can be seen that there is an increase in operating costs when including non-compliance with demand management. On the other hand, it is important to note that the increase in costs shows a non-linear behavior, since it could be expected that with a higher percentage of non-compliance there would be a greater increase in costs.

The non-linearity of this case study can be seen by comparing the cases with 33 % and 66 % non-compliance. For a deviation band of 25 % (small consumption deviation) of ω_2 there is a higher cost increase when the non-compliance is lower. This shows that the impact of non-compliance has a high variability in terms of which deviation occurs, and consequently the increase in costs is different in each case.

This first result shows the impact that non-compliance can have on a system. By identifying these variations in costs, the impact is then studied again, but increasing the number of manageable users. The increase in manageable users gives more room for non-compliance, so in these cases a greater variation in costs is expected.

4.1.2.2. 66 % of manageable users

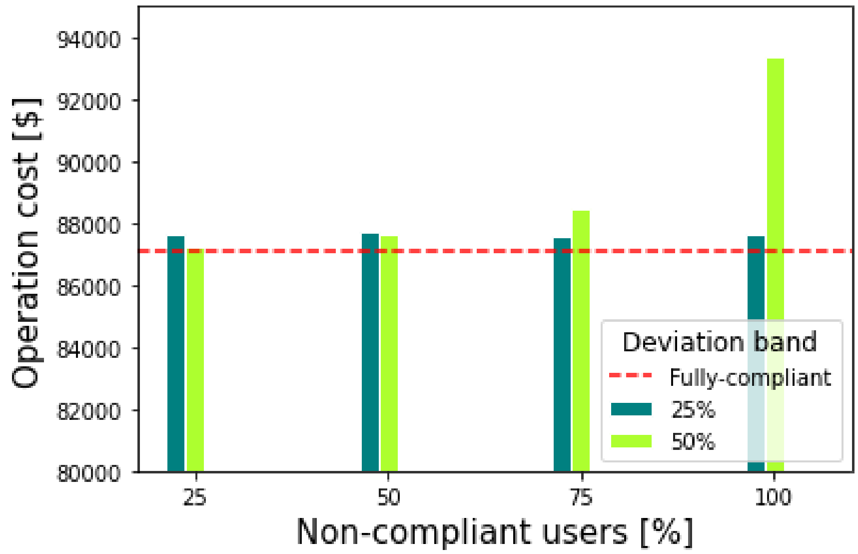


Figure 4.4: Four buses system, 66 % of manageable users: expected operation cost vs. real operation cost.

As in the first case, the results in figure 4.4 show that in all cases where there is non-compliance there is an increase in costs. This is attributed to the fact that non-compliance shifts the time slots in which the appliances are used based on the importance it places on their well-being. On the other hand, the changes in elasticity resulting from the change in the importance that the user gives to their well-being generate changes in the setpoints of the thermostatically controlled appliances.

On the other hand, it is observed that in the scenario with non-compliance of 100 % there is a steeper increase in the operating costs. This is attributed to the use of the emergency generator, which, given its high cost, when it starts to be used there is a more pronounced increase in costs due to consumption not considered by the operator. To corroborate the above, the table 4.3 shows the energy supplied by emergency generation for the scenarios shown in figure 4.4. In the table, scenario 8 shows a significant increase in the energy supplied by the emergency generator.

Table 4.3: Four buses system, 66 % of manageable users: Operation costs and emergency generator use.

Scenario	Manageable users	Users with non-compliance	ω_2 band	Expected cost	Real cost	Emergency generator use[MWh]
1	4/6	1/6	25 %	87,104.1762	87,639.323	0.000
2	4/6	2/6	25 %	87,104.1762	87,739.8413	0.000
3	4/6	3/6	25 %	87,104.1762	87,592.1373	0.000
4	4/6	4/6	25 %	87,104.1762	87,626.6848	3.514
5	4/6	1/6	50 %	87,104.1762	87,234.7754	0.000
6	4/6	2/6	50 %	87,104.1762	87,629.0937	0.000
7	4/6	3/6	50 %	87,104.1762	88,448.8227	10.479
8	4/6	4/6	50 %	87,104.1762	93,396.7331	45.321

4.1.2.3. 83 % of manageable users

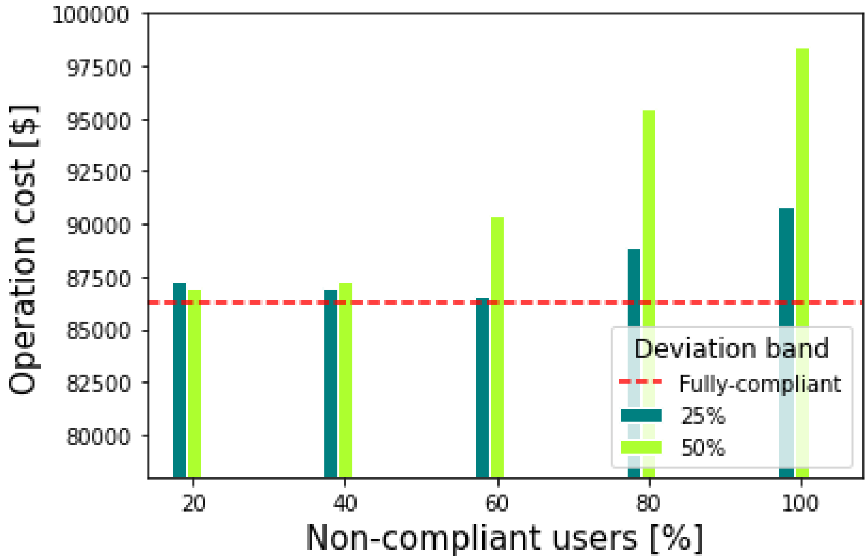


Figure 4.5: Four buses system, 83 % of manageable users: expected operation cost vs. real operation cost.

The results for the case shown in figure 4.5 are similar to the previously obtained. The increase in operating costs are maintained. Also, the steeper increase in operating costs is maintained when the use of the emergency generator increases, as shown in Table 4.4.

On the other hand, there is evidence that if the deviation band of ω_2 is larger, there is a tendency for the increase in costs to be more pronounced. This is because a larger deviation band implies a demand curve further away from the one expected by the operator. So that if this occurs for all non-compliant users in aggregate, it results in a demand profile of the system more different from the expected one, than the one that would be obtained with a smaller deviation band of ω_2. Because of that, it is more likely that the expected operation obtained from the demand without non-compliance is further away from the optimum considering the real demand of the system.

From the cost increase the correlation that non-compliance has with the energy supplied by the emergency generation is evident. Therefore, the figures 4.6 and 4.7 illustrate what happens with the energy of the emergency generation in each scenario.

Table 4.4: Four buses system, 83 % of manageable users: Operation costs and emergency generator use.

Scenario	Manageable users	Users with non-compliance	\omega_2 band	Expected cost	Real cost	Emergency generator use [MWh]
1	5/6	1/6	25 %	86,230.0838	87,242.6653	2.092
21	5/6	2/6	25 %	86,230.0838	86,983.2352	2.092
23	5/6	3/6	25 %	86,230.0838	86,608.9077	2.092
25	5/6	4/6	25 %	86,230.0838	88,931.1337	24.092
27	5/6	5/6	25 %	86,230.0838	90,786.1627	26.934
28	5/6	1/6	50 %	86,230.0838	87,015.11247	2.092
22	5/6	2/6	50 %	86,230.0838	87,309.2992	2.092
24	5/6	3/6	50 %	86,230.0838	90,410.132	31.058
26	5/6	4/6	50 %	86,230.0838	95,475.5158	68.480
28	5/6	5/6	50 %	86,230.0838	98,374.8439	76.880

4.1.2.4. Energy supplied by emergency generators

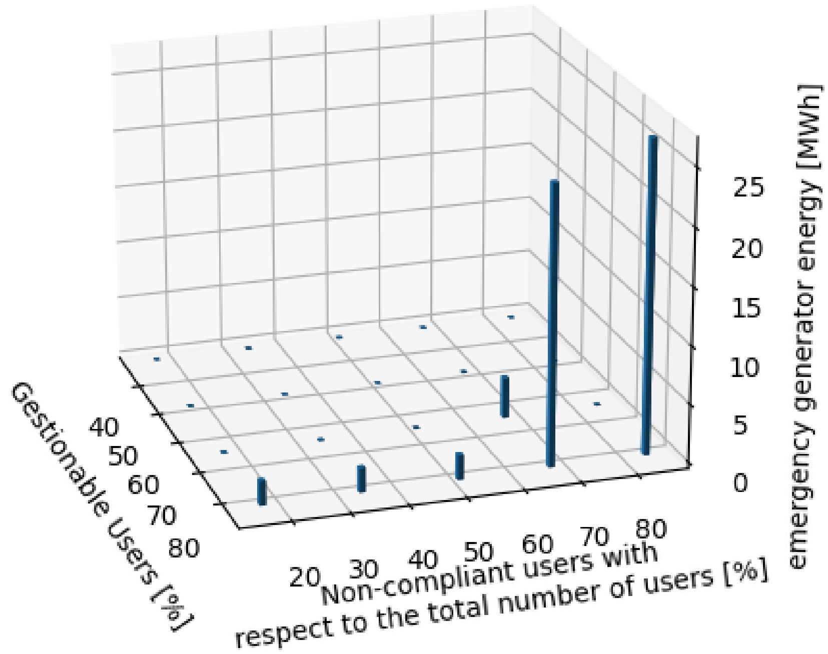


Figure 4.6: Four buses system: Energy supplied by emergency generators due to non-compliance with up to 25 % deviation of ω_2 (small consumption deviation).

Based on the above graph, it can be inferred that with a higher number of users who do not comply with the demand management program, the amount of energy supplied by the emergency generator increases. This can be observed in the cases with a higher percentage of non-compliance, where more pronounced buses are observed in the graph. This more pronounced buses were originated by a gap between the expected and real demand. For high levels of non-compliance, this gap is large enough for the emergency generation to supply more than 20 [MWh].

On the other hand, in Figure 4.6 it is also possible to note that with a higher percentage of users with managed demand there is a greater use of the emergency generator. This is evident when comparing the case with 83 % of manageable users with the cases where the aforementioned percentage is lower. Given different levels of managed demand, for the same percentage of non-compliance, different levels of energy supplied by the emergency generation are observed. In relation to the above, for this case study it is possible to note that when 83 % of the users are managed, emergency generation is used for all cases of non-compliance, as opposed to the cases with a lower number of managed users.

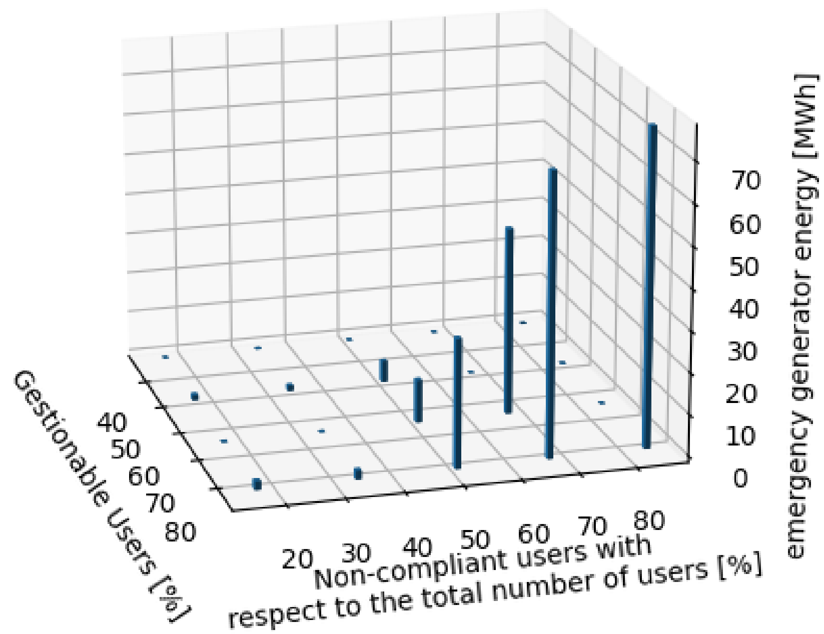


Figure 4.7: Four buses system: Energy supplied by emergency generators due to non-compliance with up to 50 % deviation of ω_2.

By increasing the deviation band of the values of ω_2 the tendency of the results is the same. However, the magnitude of the energy that is supplied through emergency generators is greater. This because a greater deviation of the consumption curve means a consumption curve that differs considerably from the expected one.

Contrasting figures 4.6 and 4.7, it can be observed that a higher deviation band of ω_2 implies, in most of the cases, a higher use of emergency generators. This higher use of emergency generators leads to higher cost increases, as can be seen in the critical cases for the different ω_2 deviation bands. This happens because when considering a greater deviation band, the demand curve has more space to deviate.

From the results of this case study, it is possible to note that non-compliance in demand management does have an impact on the operation of the system. For this reason, it was decided to carry out a study in a more complex system to study a greater number of scenarios, seeking to give more depth to the analysis. For this, the system was changed to one with a greater number of buses and users.

4.2. 24-buses system

4.2.1. System Description

For a more in-depth analysis of the second case study, simulations were carried out on a twenty-four buses system. The constructed system has seventeen generators, forty five transmission assets, and multiple demands distributed over its twenty four buses. This (and the previous) case study was an hypothetical system. In spite of being a hypothetical system, the analysis and the tendency of the results is applicable to systems that are in the same situation of the study, taking into account the conformation of each system. The latter is supported by the sensitivity analysis performed.

Fifteen standard users were considered in the system. These users were distributed between manageable and non-manageable depending on the scenario in which it was worked. Each standard user represents ten thousand users in the grid to achieve a level of consumption comparable to the generation of the system machines. In appendix A is available the information of each scenario and the users that are in non-compliance. When a manageable user was not complying with the demand management, the values of ω_2 set out in table 4.5 were used. On the other hand, different generation mixes were considerate. All mixes have Diesel, Coal, LNG and solar, and some also included wind generation (wind turbine generation on appendix C).

Table 4.5: ω_2 values for twenty-four buses system.

User	Original ω_2	new ω_2 [-25 %,25 %]	new ω_2 [-50 %,50 %]
1	0.5	0.71	0.93
2	0.5	0.58	0.67
3	0.7	0.51	0.32
4	0.3	0.45	0.6
5	0.5	0.69	0.87
6	0.7	0.48	0.26
7	0.3	0.36	0.43
8	0.5	0.32	0.15
9	0.7	0.67	0.64
10	0.5	0.72	0.94
11	0.4	0.3	0.2
12	0.3	0.08	0.01
13	0.85	0.97	0.99
14	0.3	0.41	0.52
15	0.3	0.14	0.01

Having defined the users and the system, it remains to define the solar and wind generation, the ambient temperature and the price signal. The previous information is maintained with respect to the previous case study, except for the solar generation, where having a higher capacity of this type of generation results in higher power from these resource, but with the same profile.

4.2.2. Sensitivity analysis

Similar to the first case study, three variables are modified for the sensitivity analysis: number of manageable users, number of users that do not comply with the demand management program, and the deviation band of ω_2 that non-compliant users will have.

Since a more complex system is involved, it is possible to analyze a larger number of scenarios, whose results, case by case, are shown in the appendix A. The following graphs summarize the results obtained from the sensitivity analysis of the first generation mix for different system metrics. The results for the remaining mixes can be found in Appendix A.

- Operating cost.
- Cost overrun [%].
- Energy supplied by emergency generators.

4.2.2.1. Operating cost

The results obtained for operating costs given different scenarios of non-compliance with demand management are shown below. For each scenario four values were considered for comparison:

- Expected operating cost: Operating cost obtained from a real demand equal to the expected demand.
- Operating cost without demand management: In addition to demand management, a scenario is simulated in which there is no demand management. In this scenario the user maximizes his welfare without considering the price signal when defining his consumption curve.
- Operating costs with non-compliance of up to 50 %: Non-compliance was included in the demand management, considering a high consumption deviation, through a deviation band of ω_2 of 50 %. For simplicity, the scenario with this deviation is also called "big consumption deviation", since this deviation band means a considerably different willingness to participate in demand management.
- Operating costs with non-compliance up to 25 %: Non-compliance was included in the demand management, considering a small consumption deviation, through a deviation band of ω_2 of 25 %. For simplicity, the scenario with this deviation is also called "small consumption deviation", since this deviation band means a slightly different willingness to participate in demand management.

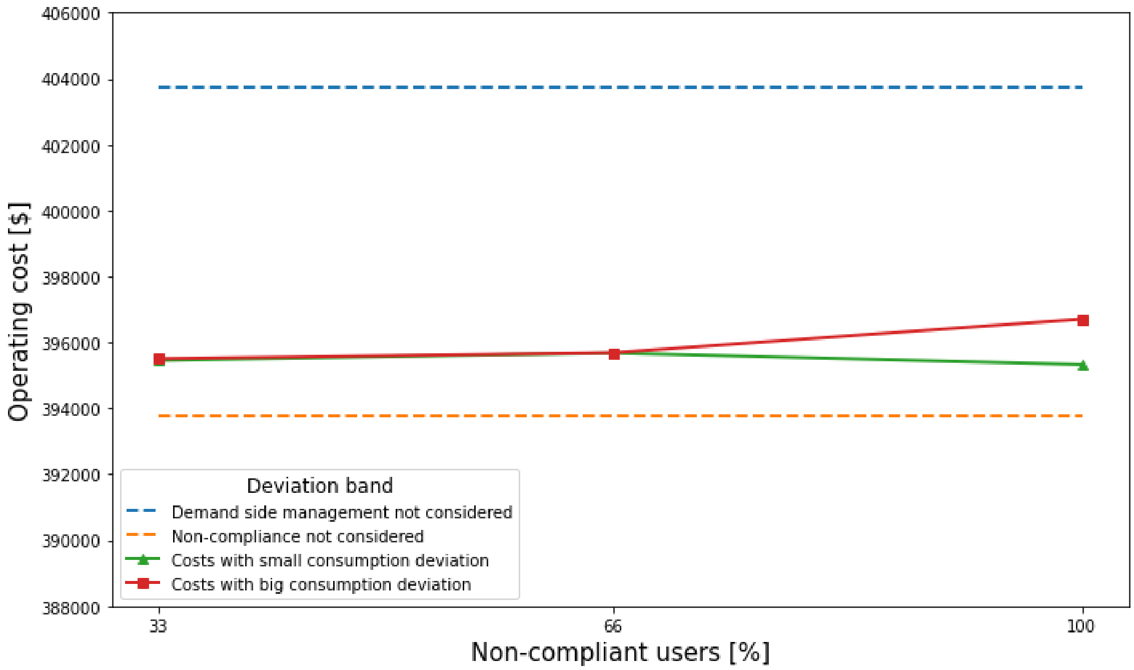


Figure 4.8: Twenty-four buses system, 12 % of manageable users: Operation costs for different scenarios of non-compliance.

Figure 4.8 shows the evolution of operating costs for different cases of non-compliance when considering a management of 12 % of the users. In these cases it can be seen that non-compliance generates a similar increase in operating costs for the small and high consumption deviation (25 % and 50 % deviation bands for ω_2). The similarity of the results obtained for both bands is attributed to the fact that, since this system has a larger number of users, when deviating from the value of ω_2 for a low number of users, it does not generate a considerable impact on the grid. This because the real demand is similar to the expected demand, despite the non-compliance.

On the other hand, the cost increase is not sufficient to reach the obtained cost of demand management. However, it does show a reduction in the cost savings gap. It is important to note that for this and the following graphs, the “consumption deviation” is not forced directly, it is originated from the aforementioned deviations of ω_2, since ω_2 reflects the willingness to participate.

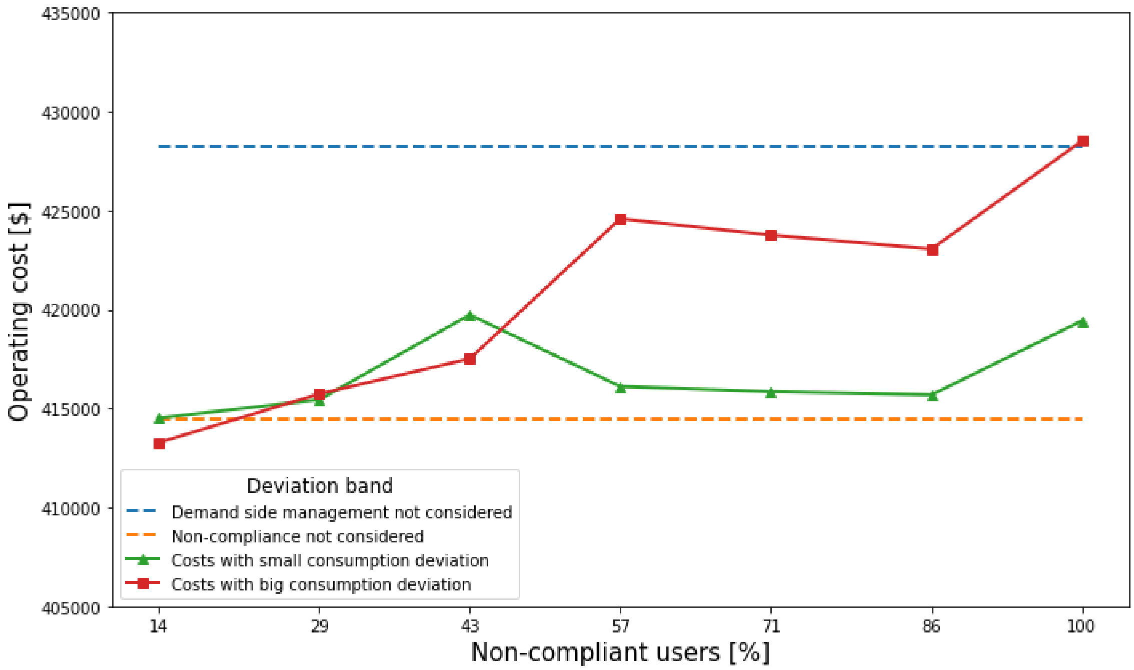


Figure 4.9: Twenty-four buses system, 28 % of manageable users: Operation costs for different scenarios of non-compliance.

Compared to the results in Figure 4.8, Figure 4.9 begins to show the contrast in costs obtained for different bands of deviation from ω_2. If a deviation of 25 % is considered (small consumption deviation), the increase in costs remains close to the expected cost, while using a band of 50 % (high consumption deviation) operating costs move away from the expected cost as the non-compliance increases, becoming closer to the operating cost without applying demand management.

This result may have practical implications when applied to a system, since part of the objectives of demand management is the reduction of operating costs. From the graph it is evident that, from a certain level of non-compliance, the cost savings gap between cases with and without demand management may be considerably reduced, reducing savings and even reaching 0 when non-compliance with demand management reaches critical values.

It should also be noted that for the case in which the non-compliance is 14 % lower operating costs are observed than the ideal case. This reduction in costs shows that deviations could also benefit the network in particular situations. This occurs when, as a result of non-compliance, the adjustments in the consumption time slots make it possible to reduce the consumption of expensive machines in other hours, or to take more advantage of renewable energies.

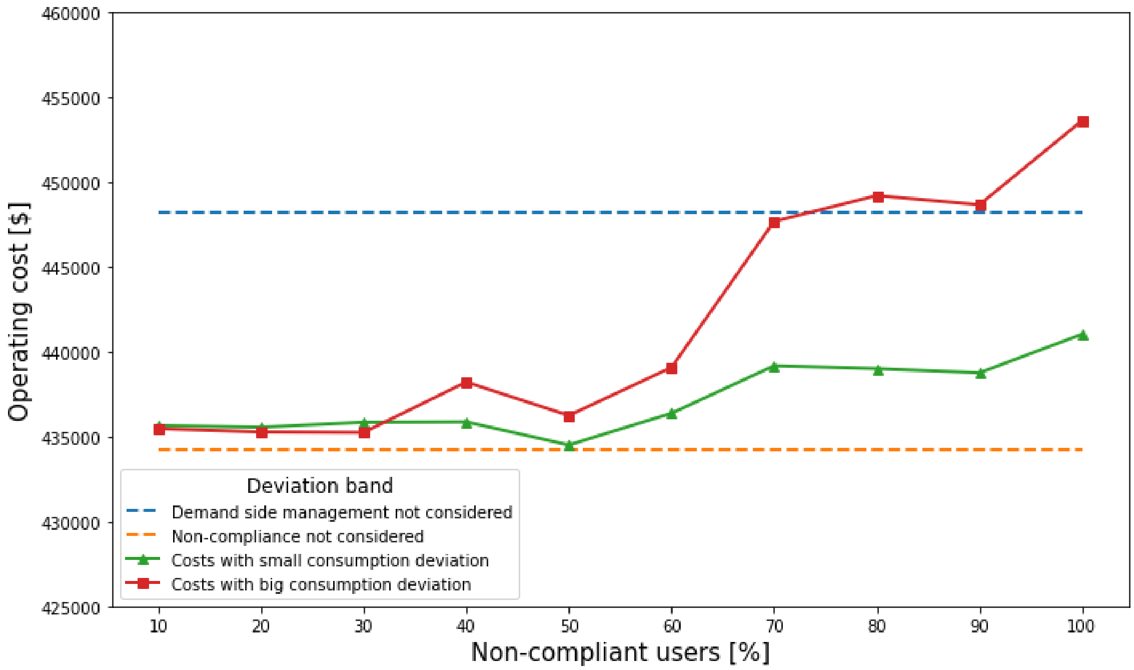


Figure 4.10: Twenty-four buses system, 40 % of manageable users: Operation costs for different scenarios of non-compliance.

Figure 4.10 shows one of the less desirable consequences that can result from non-compliance with the demand management program, which is a higher operating cost even than in the case with no demand management. As in the previous case, non-compliance generates an increasing cost growth as the percentage of users that do not behave as expected increases. For a ω_2 deviation band of 50 % (high consumption deviation), when non-compliance reaches 75 % an operating cost equal to the operating cost without demand management is obtained, and from that point onwards the operating cost always turns out to be higher than the cost without demand management.

The results obtained in the previous graph show that even though demand management is a useful tool in electric grids, it may harm the grid if user behavior is not properly understood. If the user's behavior and a potential non-compliance with the demand management program cannot be accurately determined, it can generates an impact on operating costs of the grid. Even reaching scenarios where it is convenient, from an economic perspective, not to perform demand management.

It is also important to contrast the difference between the two deviation bands studied. The graph shows that when the consumption deviation is small (deviation band of 25 % for ω_2) there is also an increase in operating costs, but the cost without demand management is never reached. This result shows that there is a critical deviation band in the system for the different amounts of non-compliance users. From this it is possible to infer that each system will have its own critical deviation band and a critical amount of non-compliance demand. For the case study, the small consumption deviation band is not critical, unlike the high consumption deviation, which is critical as multiple scenarios are identified in which the operation reaches a higher cost than the case without demand management.

This result shows the value that the study can provide to demand aggregators. By replicating this study, and knowing the amount of demand that is being managed in a system, it is possible to know which is the tolerable deviation by a user, and take actions based on this value to avoid negative impacts on the grid.

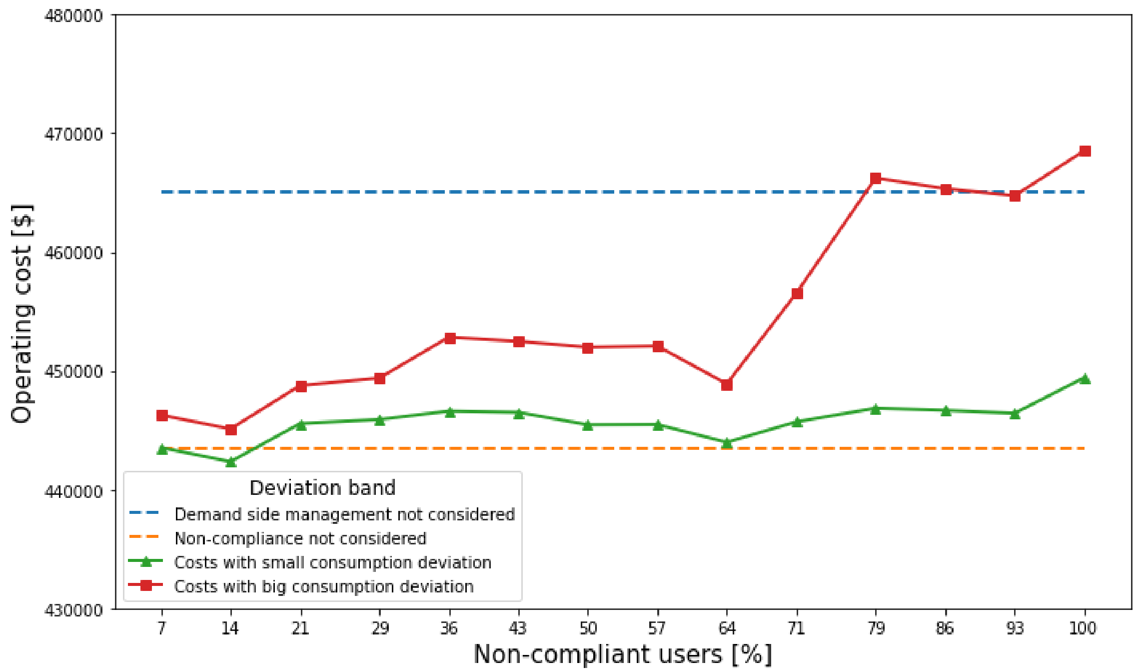


Figure 4.11: Twenty-four buses system, 56 % of manageable users: Operation costs for different scenarios of non-compliance.

For the case of figure 4.11, the results show the same trend as those obtained in figure 4.10. However, the increase in costs is less pronounced and once the point where the cost of operation with non-compliance is greater than or equal to the cost without management is reached, the gap with respect to the yellow curve is less pronounced than in the previous case. This shows that the impact of non-compliance is not linear, since it could be expected that a higher level of non-compliance, given a greater amount of managed demand, will generate a greater impact than a lower level of non-compliance. However, this case shows that this is not necessarily the case, and the impact generated in the system depends on how the demand curve of the different users is modified.

On the other hand, it is important to note that for this case and those previously studied, when the percentage of non-compliance is lower, the impact on costs is small and even though the gap between the cost with and without demand management is narrower, it is still convenient to use demand management. Therefore, the cost overrun makes demand management inconvenient only in the most critical scenarios of non-compliance, considering also the variability that exists in each particular case and in each system.

From the cost graphs it is evident that for low non-compliance percentages, demand management continues to be convenient for the system despite the fact that it may reduce the savings obtained. On the other hand, as the amount of managed demand increases, since it represents a larger amount of the total system, the cost increase is more pronounced. In addition, from a practical point of view, there is more room for non-compliance with more manageable users, resulting in a greater risk of increasing the operating costs.

4.2.2.1.1. Operating cost with fixed non-compliant users

Another interesting visualization of the results obtained is how a fixed non-compliance percentage affects different levels of demand management. Below are two graphs showing how a fixed non-compliance percentage impacted in the case study. Once the percentage of users that will not fulfill their consumption promises is fixed, the percentage of users that participate in demand management is increased, keeping the non-compliance percentage fixed. In this way, it is possible to visualize the impact of the non-compliance percentages in the case study system.

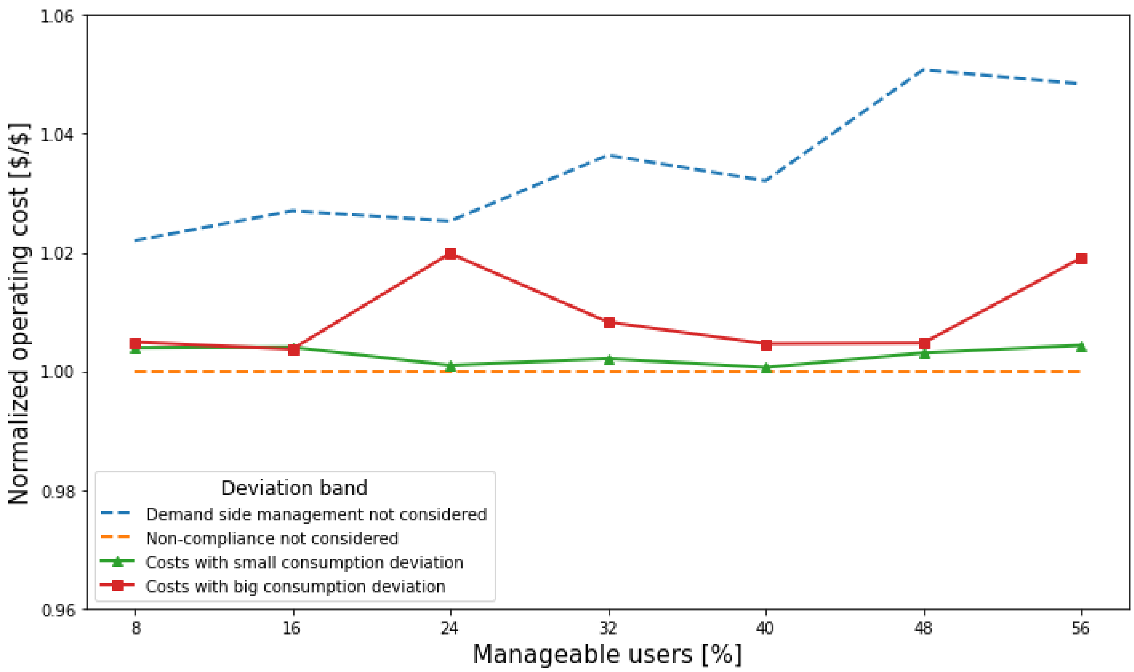


Figure 4.12: Opearting costs for different percentages of manageable users, considering 50 % of non-compliant users.

When considering a non-compliance of 50 %, we note that for the case study the cost without considering demand management is never exceeded. This occurs for both ω_2 deviation bands used, from which it is inferred that for both deviation bands demand management is beneficial even considering a 50 % of non-compliant users. However, it is important to note that when the deviation in users consumption is higher, the savings obtained through demand management are lower. Finally, we can observe from the curves that given a fixed percentage of non-compliant users, a greater amount of managed demand does not mean a greater impact of this non-compliance.

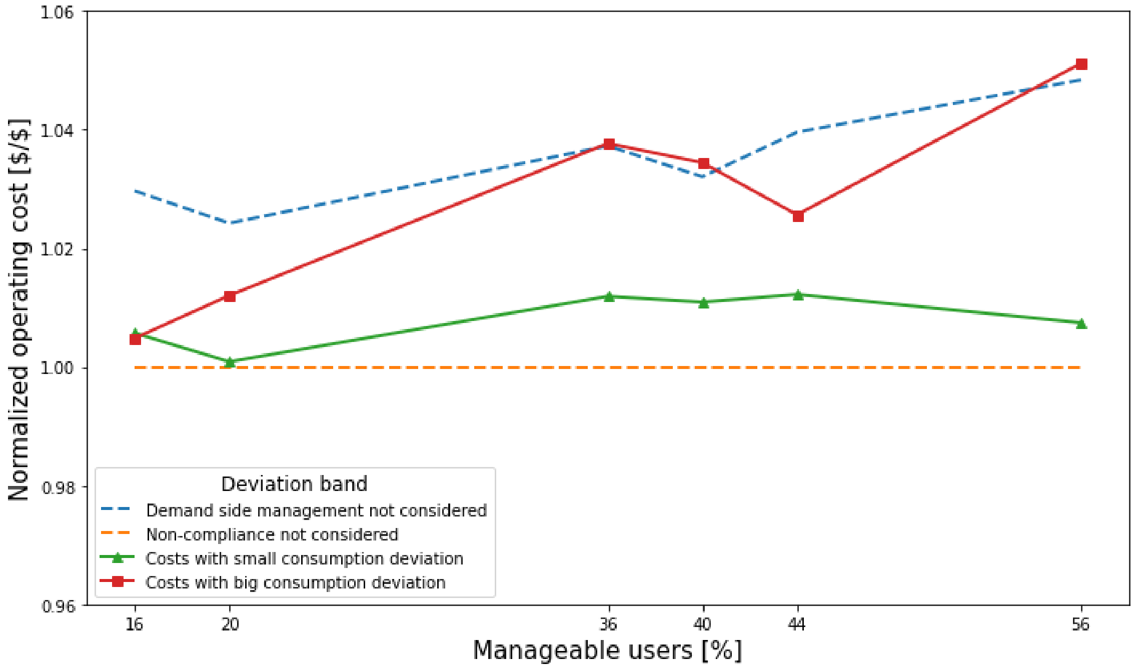


Figure 4.13: Opearting costs for different percentages of manageable users, considering 80 % of non-compliant users.

In contrast to Figure 4.13, this figure does show scenarios in which the operating cost without considering demand management is exceeded. The operating cost without considering demand management is exceeded when a large deviation band (50 % deviation from ω_2) is considered. In such cases, demand management is no longer convenient in economic terms, from which it is inferred that for the system under study an 80 % non-compliance is more than what can be tolerated, especially when the percentage of managed demand is high. On the other hand, when the deviation in user consumption is small, demand management is still convenient despite the high percentage of non-compliance. From this it can be inferred that if the deviation in consumption is small, the system can tolerate it even if the percentage of non-compliance users is high.

Figures 4.13 and 4.12 show two results of interest for the case study:

- When the consumption deviation is small, no matter how much demand we manage or the percentage of non-compliance users, demand management is always convenient in the case study. This is confirmed by bringing the percentage of non-compliance users to values close to the limit, such as 80 %.
- If the consumption deviation is high it cannot be guaranteed that demand management will be economically convenient. In Figure 4.12 this is evident as the cost without demand management was exceeded for several percentages and in Figure 4.13 it was close to being exceeded.

From these results it can be inferred that the magnitude of the deviation may be more influential than the number of users in non-compliance. In other words, all users could even be allowed to breach their consumption promise, as long as the deviation in their consumption is small. What is stated in this part of the results can be summarized in one sentence: It may be preferable that many users deviate little than few users deviate a lot.

4.2.2.2. Cost overrun

As a complement to the results presented in section 4.2.2.1, this section presents the percentage variation in operating costs for the different non-compliance scenarios.

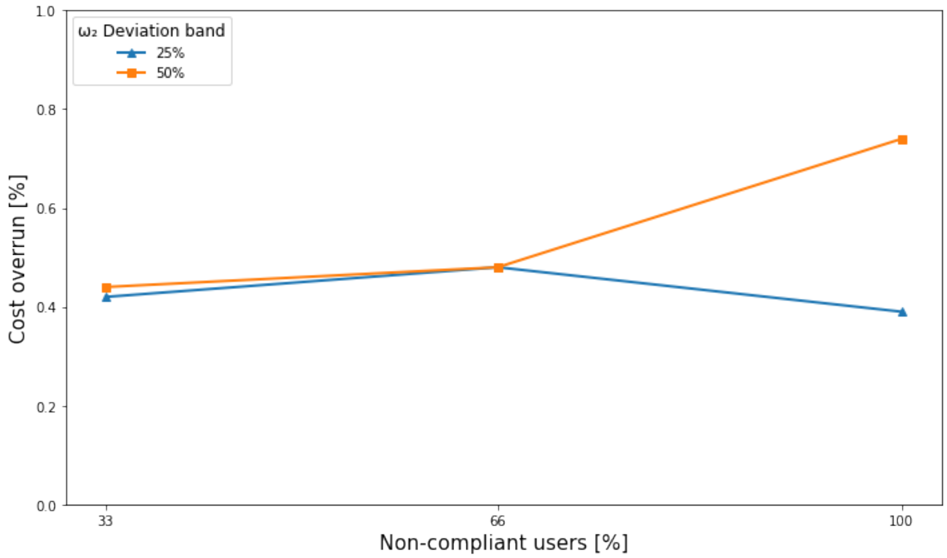


Figure 4.14: Twenty-four buses system, 12 % of manageable users: Percentage cost overrun.

Figure 4.14 shows the evolution of cost overruns when demand management percentage in the system is low. In this case, the aforementioned is evident, which is that for low levels of non-compliance the system makes its operation more expensive, but the impact is minor, as shown in this graph, where the maximum cost overrun reached is 0.74 %.

The low percentage of cost overruns obtained shows that for a demand aggregator that concentrates a low amount of system consumption, the aggregator can be more permissive with respect to non-compliance. This tolerance is feasible because for the scenarios studied the cost overruns do not bring the new operating costs close to the threshold at which demand management ceases to be convenient. However, non-compliance for these low percentages of managed demand is still undesirable because it reduces the savings gap, which is not beneficial for the system or for the aggregator, which could pass this impact on to users.

It is important to emphasize for the results of this section the tendency of the curves obtained, which are analogous to those obtained in section 4.2.2.1. The difference is that by measuring percentages of costs instead of net costs, the impact of non-compliance on the grid can be more clearly visualized.

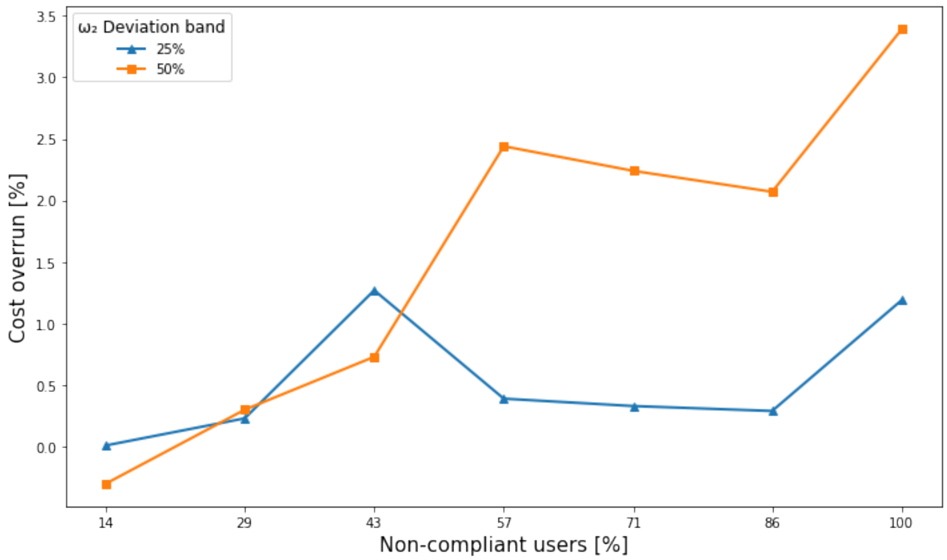


Figure 4.15: Twenty-four buses system, 28 % of manageable users: Percentage cost overrun.

As the number of manageable users increases to 28 %, as shown in Figure 4.15, the tendency of the results to increase non-compliance becomes evident. This tendency is towards an increase in system operating costs, mainly due to the use of emergency generators to supply the load whose consumption could not be supplied from the operation established. This is evident when a deviation band of 50 % is used for ω_2, reaching a cost overrun of over 3 % in the most critical case of non-compliance.

It should be noted that although 3 % may be considered a small percentage, this impact can be considered significant. This is because the 3 % increase in costs is sufficient to reach the threshold where the savings gap is lost, reaching an operating cost higher than the cost without demand management.

Another important result obtained from this graph is the evolution of the curve for a 25 % deviation band, where higher levels of non-compliance do not necessarily imply a greater impact on grid costs. It can be seen that the maximum of this curve is reached for a non-compliance of 43 % of users. This shows that the impact of non-compliance on the grid depends on each case, which can be advantageous since it may be that for high levels of non-compliance the impact is lower than expected. However, the opposite may also be the case as shown in this graph, where for a low level of non-compliance the impact is higher.

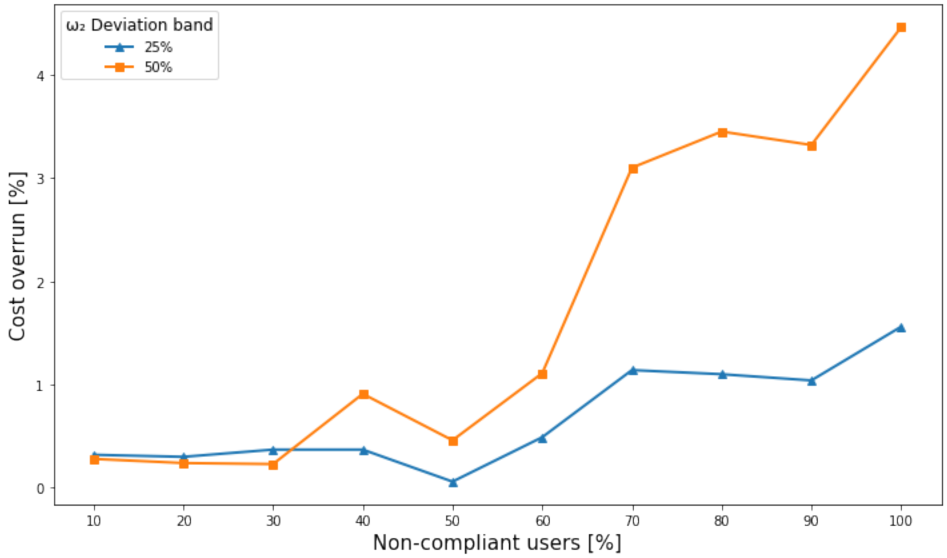


Figure 4.16: Twenty-four buses system, 40 % of manageable users: Percentage cost overrun.

The results shown in Figure 4.16 maintain the tendency of those obtained previously in this section and in Section 4.2.2.1. A greater impact on operating costs is expected for the higher deviation band of ω_2. On the other hand, for the scenarios shown in the previous graph, the magnitude of the cost overrun reaches a maximum close to 4.5 %. This percentage can be significant at the time of operating a grid. a cost overrun of this magnitude can mean that it is more convenient to operate the grid without demand management in the event of a non-compliance of such magnitude, which is what happens in the case just described. This is more evident if contrasted with Figure 4.10, where after a certain point the cost overrun is such that the cost of operation considering non-compliance is higher than the cost without demand management.

Contrasting the previous situation with respect to cost overruns when the amount of demand managed is 12 %, in this case, an aggregator that concentrates 40 % of the demand in the system studied cannot be permissive with respect to non-compliance with a deviation of up to 50 %. Given the high amount of demand it handles, if users deviate from their promised consumption there will be a considerable reduction in the savings expected from demand management.

To prevent this from happening, the aggregator must ensure that the number of non-compliance users is low, or that the band in which users deviate does not exceed 25 %. The latter, because for this deviation band, lower cost overruns are observed, which do not reach the operating costs without considering demand management.

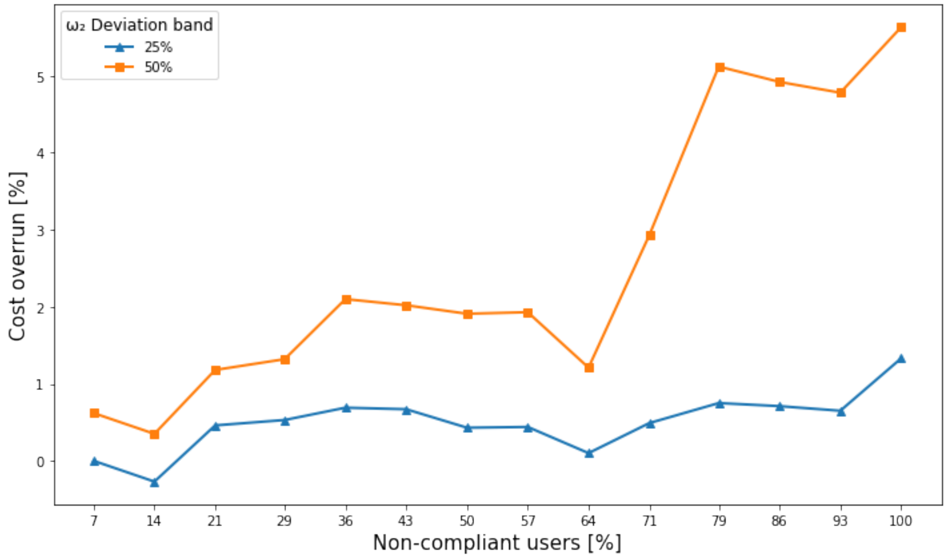


Figure 4.17: Twenty-four buses system, 56 % of manageable users: Percentage cost overrun.

The tendency in the results shown in Figure 4.17 is the same as that observed in the previous graphs. For a higher non-compliance, a higher percentage of cost increase was obtained, always considering the variability that occurs in each case depending on which non-compliance scenario is occurring in the system.

It is also important to note that when considering a deviation band of 25 % for ω_2 for a non-compliance level of 14 %, it is noted that the cost overrun is negative, which means a reduction in operating costs when considering non-compliance. This occurs because the non-compliance considered in the users can be an increase or decrease in the importance of their welfare over what the system operator indicates. In the case that some users reduce the importance of their welfare, the schedules in which some appliances are used are adjusted in a way that these are the most convenient for the grid, in addition to reducing the consumption associated with thermostatically controlled appliances. When this occurs, there may be a cost reduction in the system despite the non-compliance.

Although there are users who give greater importance to their welfare than expected, there are also users who behave better than expected, so there may be cases in which the balance of these non-compliances is beneficial to the system. However, as could be seen in the graphs shown above in this section it is very unlikely that this happens because a better than expected behavior will not necessarily be good for the grid. An example of the latter is that a user, giving less importance to his well-being, changes the hours in which he uses certain appliances to favor the operation of the grid. However, since the operator considered a different behavior of the user, the system was prepared for his appliances to be turned on at different times than those in which they were actually turned on.

On the other hand, from the graphs shown in this section it is possible to notice that when a higher deviation band is used, the cost overruns are higher in most of the scenarios. This result is consistent with what is expected, since a higher deviation by part of the users means a demand curve farther away from the expected one, which results in an operation further away from the optimum.

From the results presented in this section, it is possible to note that the percentage increase in costs due to non-compliance for low levels of non-compliance is not significant. However, as the number of users who do not behave as expected increases, this percentage increases and, although it does not reach extremely high values, it can result in a cost overrun such that the operation without demand management is more convenient than when considering demand management and non-compliance of the users. From the latter, it can be inferred that non-compliance in demand management programs can have a negative impact on system operation for high percentages of non-compliance.

4.2.2.3. Energy supplied by emergency generators

This section presents the results of the use of emergency generators for different scenarios of non-compliance with the demand management program, where the correlation with the increase in operating costs is analyzed.

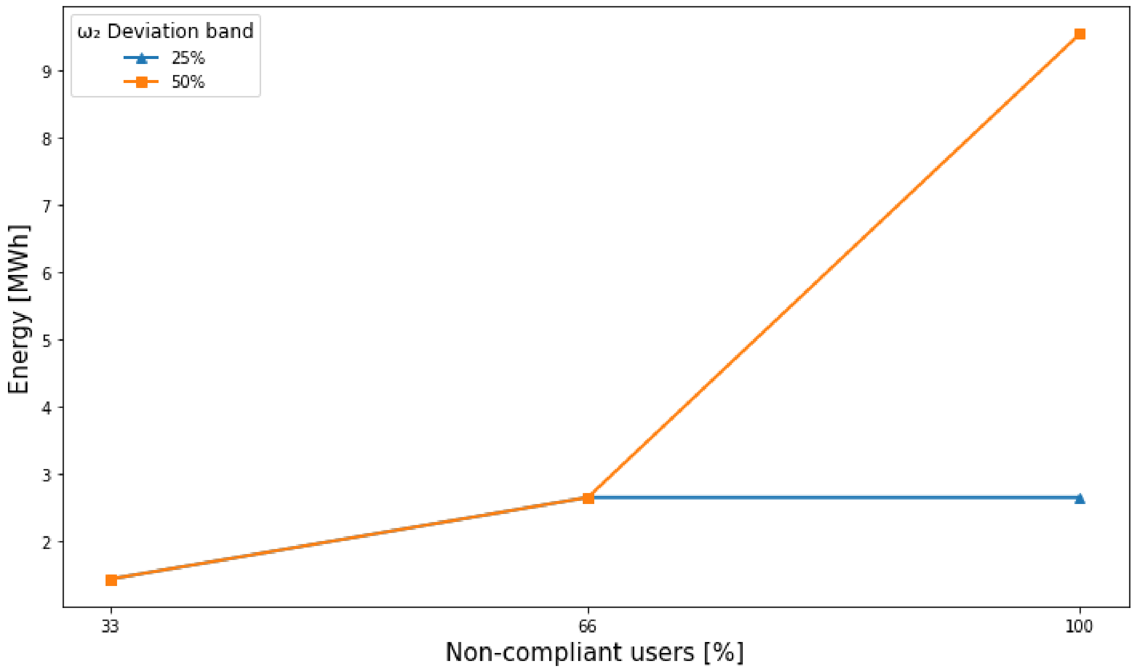


Figure 4.18: Twenty-four buses system, 12 % of manageable users: Energy supplied by emergency generators.

A comparison of figure 4.18 with figure 4.14 shows the similarity of the two graphs, and infers that the increase in operating costs is directly related to the use of emergency generators. Verifying that the model behaves as expected since the use of the emergency generator is the main cause of the cost overruns.

On the other hand, it is important to note that the increase in costs is not only due to the emergency generators. Therefore, the change in the consumption of thermostatically controlled appliances and the change in the time slots of the appliances schedules modify the demand curve. This change in the demand curve means an increase in costs with respect to the expected value, due to an unexpected demand profile.

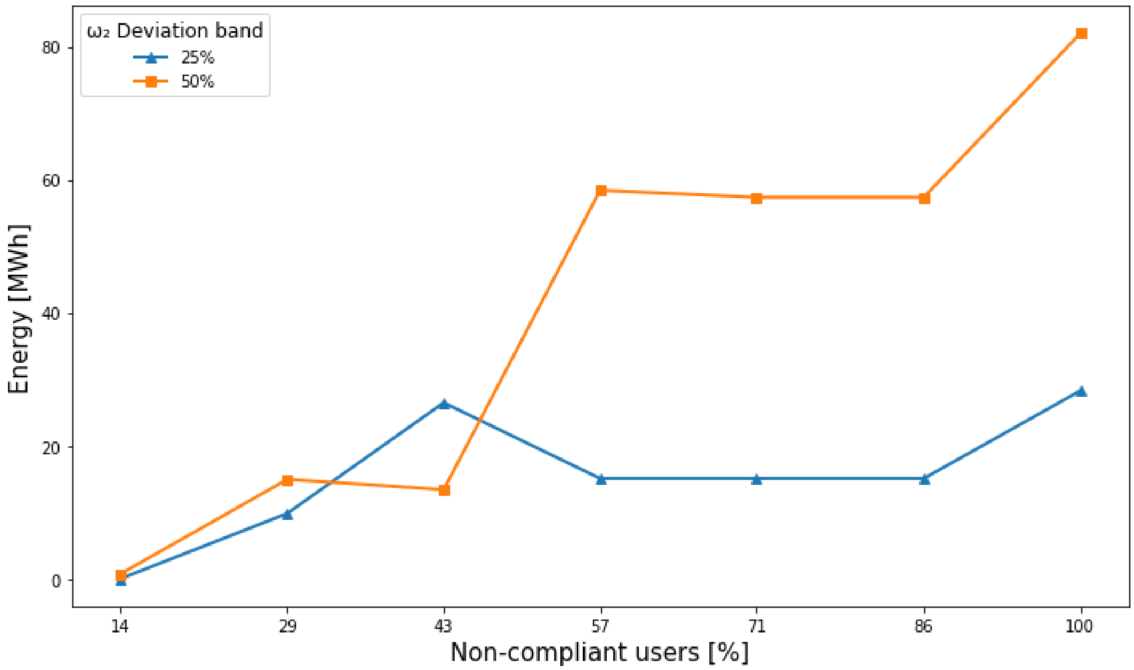


Figure 4.19: Twenty-four buses system, 28 % of manageable users: Energy supplied by emergency generators.

In the results shown in Figure 4.19 it is possible to notice that with a higher non-compliance in the demand, the tendency is to increase the use of emergency generators. This occurs in the curve for a deviation band of 50 % for ω_2, where it reaches about 80 [MWh] supplied by the emergency generator for high levels of non-compliance, as opposed to the 0 [MWh] used when the non-compliance is 4 %.

On the other hand, when the deviation band for the values of ω_2 is 25 %, it is observed that the tendency of the use of emergency generators is also increasing. However, this curve is not monotonically increasing, showing again that the impact of non-compliance on the system does not present a linear behavior with respect to non-compliance and depends on each case of non-compliance in particular. Despite the above, the results show that as non-compliance increases, the use of emergency generators may be more expected.

Another point to note in this graph is when the number of non-compliant users reaches 43 %. At this point, the use of the emergency generator for a 25 % deviation band is higher than for a 50 % band. This result can be confusing, as it is expected that a greater non-compliance will require a greater amount of energy from the emergency generator, but this is not always true. Non-compliance by different users could move consumptions to a time slot where the system is able to better address it.

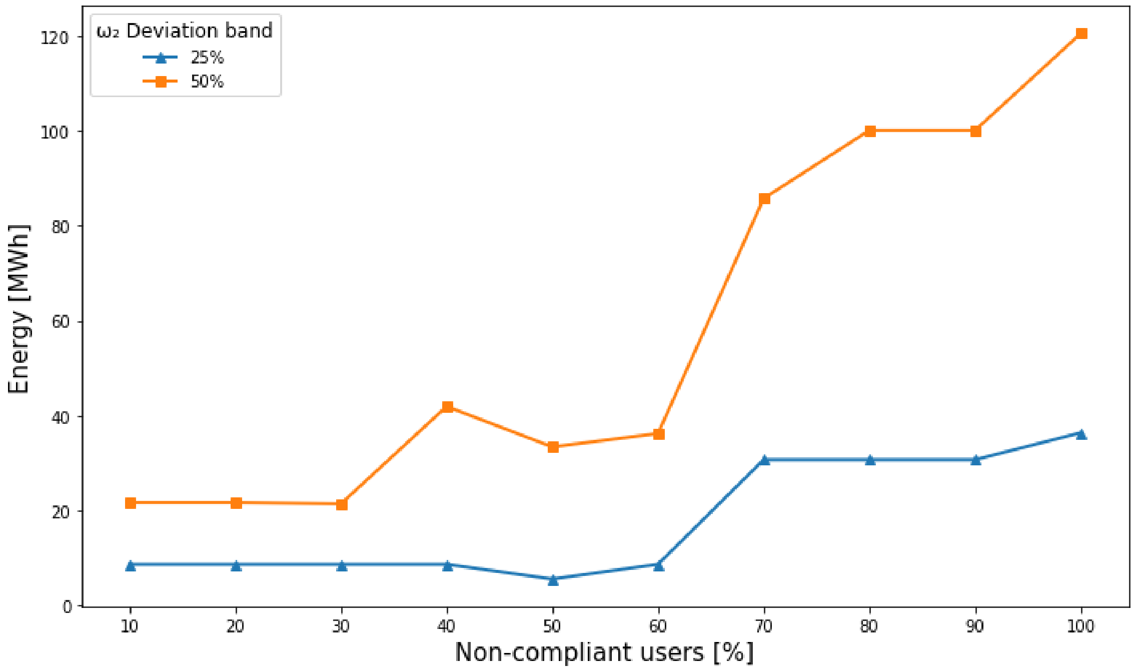


Figure 4.20: Twenty-four buses system, 40 % of manageable users: Energy supplied by emergency generators.

In the graph in Figure 4.20 the tendency on the use of the emergency generators is maintained. With a higher percentage of non-compliance there is a greater use of emergency generators. In addition, it is observed that for a higher deviation band of ω_2 there is a higher use of emergency generators, attributable to a demand curve further away from the expected one. It is important to note that the aforementioned is expected to occur about the ω_2 deviation bands, however, there may be cases where this does not occur as observed in Figure 4.19 when the non-compliance is 43 %.

Continuing with the comparison with Figure 4.19, it is possible to see another particular scenario that occurs when 28 % of the users in the case study are managed. In Figure 4.20 the use of the emergency generator exceeds 20 [MWh] close to 70 % non-compliance, while in Figure 4.19 this threshold is exceeded with 40 % non-compliance. This shows, together with its non-linear behavior, that the correlation between non-compliance percentage and emergency generator usage is not 1.

On the other hand, a comparison of Figures 4.16 and 4.20 shows that the cost overruns and the use of the emergency generator have a similar behavior. However, the curves are not identical, from which it is possible to infer that the increase in operating costs is not only attributed to the emergency generator.

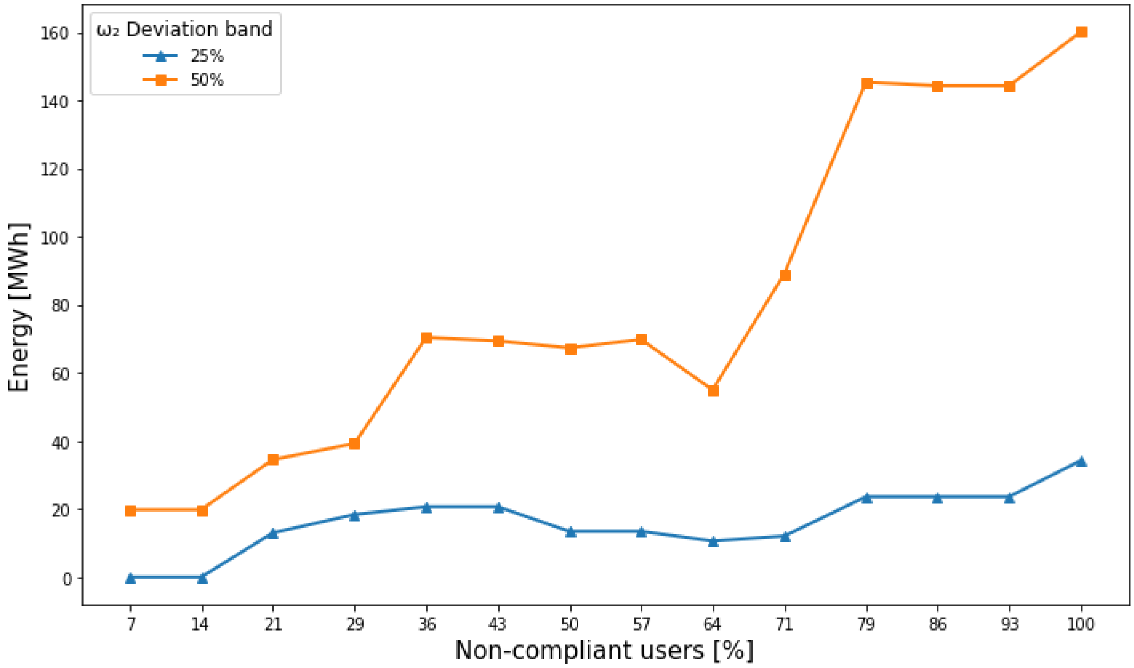


Figure 4.21: Twenty-four buses system, 56 % of manageable users: Energy supplied by emergency generators.

The results shown in Figure 4.21 are analogous to those obtained in Figure 4.20. The most remarkable aspect of these results is the high amount of energy that must be supplied by emergency generation, exceeding 100[MWh] when the non-compliance is high, which, in addition to being very costly for the system, raises questions about the capacity to supply this amount of energy that exceeds what is expected.

For the case studied it was assumed that the systems always had the necessary number of emergency generators to supply the energy that could not be delivered. However, there may be systems in which the conditions are not as mentioned above and for scenarios where non-compliance implies a high amount of energy to be supplied by emergency generators there is not enough capacity of this generation. Therefore, the loss of load would be incurred so that VoLL would have to be used, which would further increase the operating cost, also obtaining a greater number of scenarios where demand management given a certain level of non-compliance is not convenient in economic terms compared to a case without demand management.

Since the use of the emergency generator is the main cause of the cost increase, this must also be addressed by a demand aggregator participating in the system. As the aggregator is responsible for the users whose demand is being managed, it must consider how to address non-compliance to not harm the system.

The way to address non-compliance depends on the demand aggregator scheme used. For the case considered in the study, a suitable way to address non-compliance is to pass on the costs of the emergency generator to the users when their non-compliance exceeds the allowed values. This charge can be obtained from the energy used by the emergency generator, where each [kWh] that exceeds the non-compliance allowed by the aggregator, the user is charged with the cost incurred by the emergency generator to supply that energy difference.

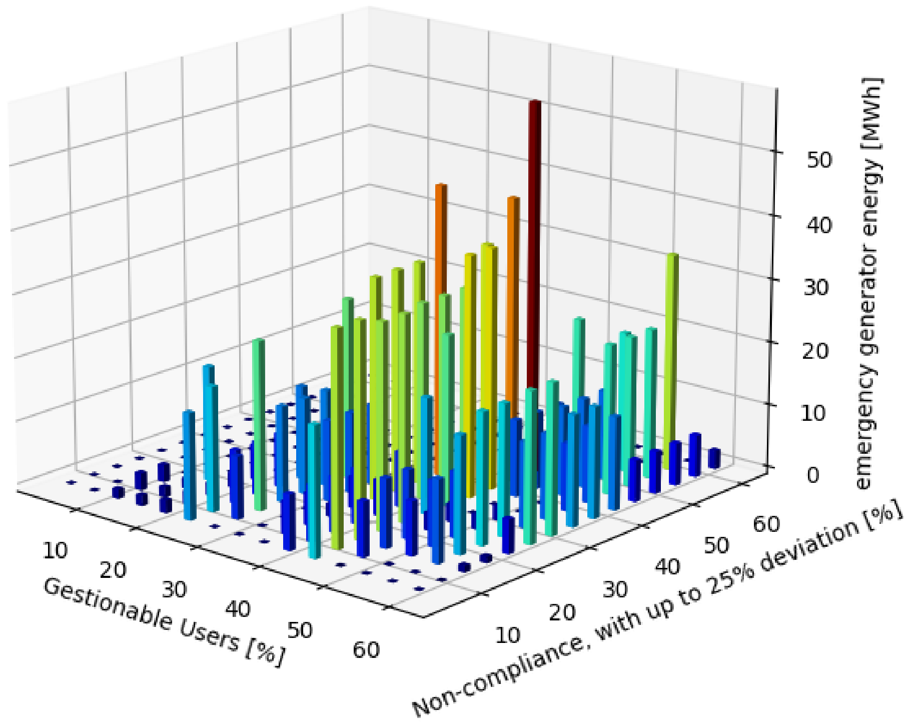


Figure 4.22: Twenty-four buses system: Energy supplied by emergency generators due to non-compliance with up to 25 % deviation of ω_2.

Figure 4.22 shows the amount of energy supplied by emergency generators for the scenarios studied where the ω_2 deviation band for non-compliance is 25 %. In this graph, the tendency is evident that for higher levels of non-compliance, a greater amount of energy is expected to be supplied through emergency generators. This is inferred from the growth of the buses as one moves along the non-compliance axis. In addition, for low levels of non-compliance, the use of emergency generators is low or null compared to cases where it increases.

On the other hand, it is also revealed the variability in the use of emergency generators depending on the scenario in which the work is done, this is evident when comparing the scenarios with 60 % of managed users with respect to the others where the managed demand is lower. When managing 60 % there is a greater space for non-compliance, in addition to a higher probability, however, for the scenarios with 60 % of manageable users it is observed that the use of the emergency generator is lower compared to the other scenarios where the level of non-compliance is the same.

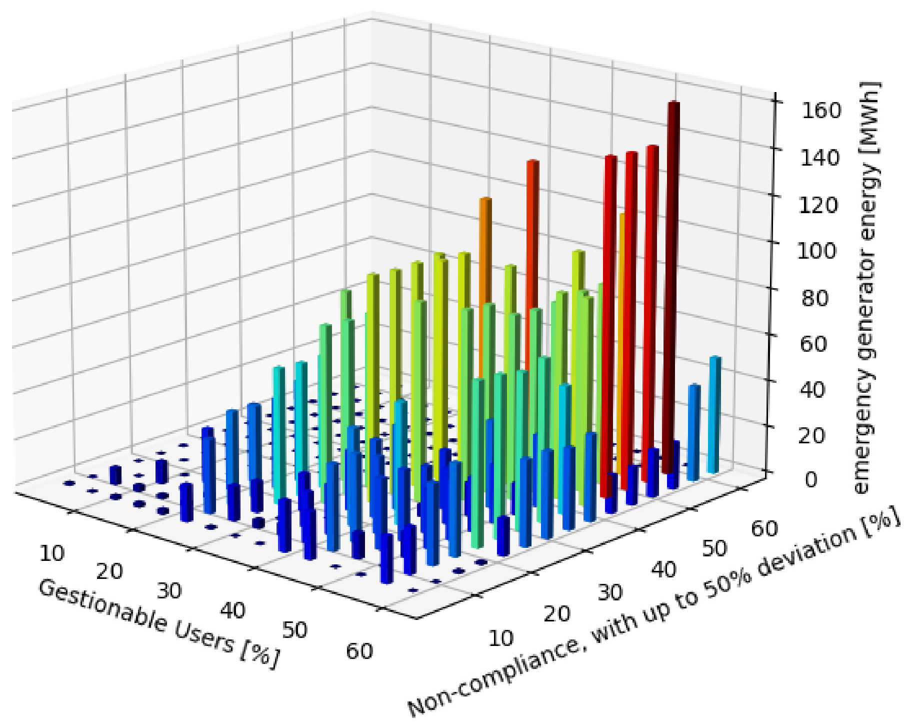


Figure 4.23: Twenty-four buses system: Energy supplied by emergency generators due to non-compliance with up to 50 % deviation of ω_2.

The results shown in Figure 4.23 correspond to the use of emergency generators for all non-compliance scenarios when the ω_2 deviation band is 50 %. Comparing this graph with the one in Figure 4.22 shows that for the higher non-compliance band, the amount of energy supplied by emergency generators tends to be higher. Being the emergency generator used up to five times more in scenarios with the same number of manageable users and non-compliance, but with different deviation bands for ω_2.

The aforementioned, added to the results shown above, make evident the importance of the ω_2 deviation band that represents the non-compliance. From the sensitivity analysis performed, it is evident that the magnitude of the ω_2 value deviation has an important influence on the impact on the grid, being determinant in defining, given a system and amount of managed demand, for what level of non-compliance demand management is no longer convenient. Therefore, as shown in the results of section 4.2.2.1, when the ω_2 deviation was 25 %, operating costs were not equalized with respect to the case without demand management, while for a band of 50 % this did occur (high consumption deviation). The results obtained show the need to create a model to estimate the non-compliance of demand management programs, to determine the critical deviation band for ω_2 in each system and thus determine whether demand management is economically convenient and what measures should be taken to minimize the non-compliance of the users.

Chapter 5

Analysis

In this chapter an analysis of the impact of non-compliance with demand management programs is made on the basis of the results presented in Chapter 4. The analysis seeks to test the hypothesis and present the main findings obtained from the case studies.

The most relevant aspect of the results obtained is that low percentage of non-compliance does not make the demand management inconvenient for the system, and in this cases demand management is always convenient in economic terms. However, high percentages of non-compliance can increase costs to such an extent that demand management is inconvenient, from an economic perspective, for the grid. This is concretely observed when comparing the operating costs for the different non-compliance scenarios, where when considering a 50 % deviation band for ω_2 there are non-compliance scenarios in which the aforementioned occurs. In addition, in cases where the operating cost does not exceed the operating cost without demand management there may also be a significant economic impact on the system, since non-compliance reduces savings in system operating costs. For the case that has non-compliant users determining whether the impact is considerable will depend on the criteria of the system operator. It is also important to note that for scenarios where non-compliance is higher, demand management can also be economically convenient despite the reduction in operating cost savings.

This identified impact on system costs can be a useful tool when making decisions regarding the implementation of demand management. If the methodology proposed is applied to a particular system, the operator can determine until which point it is convenient to apply demand management, and what impact there may be on the grid for the different scenarios. Being able to determine the impact that non-compliance with demand management programs will have on the system can be useful to take measures to reduce both the impact of non-compliance and the non-compliance itself. This can be achieved through adjustments in the operation so that a band of deviation from the demand curve is considered or through interaction with users through penalties for non-compliance with demand management programs. This penalty can be determined based on the deviation from their expected demand and the reduction in cost savings obtained from demand management. This penalty can be justified because non-compliance on the part of the users implies an operation that is far from optimum, requiring the use of emergency generators in certain cases, whose costs for the system are very high, and in critical cases could even mean the loss of load. However, this last case was not analyzed in the study.

5.1. Application in other systems

It should be remembered that the results were obtained from the simulation of a particular system. In this system, the non-compliance scenarios were modified and the generation mix was also modified. Based on these variations, multiple scenarios were generated that showed that non-compliance occurs more than in a single case. From this, it is inferred that the results obtained are applicable to other systems, since in all of them critical scenarios were identified when users did not comply with demand management.

If the methodology used in the case study is replicated in another system, the curves that determine the extent to which non-compliance in demand management is tolerable can be obtained. Considering that this is applied with the intention of validating the implementation of demand management, it can be applied in a specific system whose conditions are known. In such a system, instead of varying such conditions as was done in this study, only the non-compliance could be varied, generating multiple scenarios for a percentage of non-compliance of the managed demand.

By performing the analysis for different deviations given a non-compliance percentage, more than one different critical non-compliance percentage will be obtained for each scenario studied. From these different non-compliance percentages the grid operator can establish a criterion of up to which non-compliance percentage demand management is suitable and for which deviation band it is not suitable. This criterion depends on the system operator and could be the minimum critical percentage obtained, the average critical percentage, or other.

A practical application would be for a demand aggregator that seeks to implement demand management in a grid or microgrid. In such a case the aggregator implements the exposed methodology in the system model and through surveys develops the user models using the CREST model or another model adapted to the location where the demand management is applied. Once the system model and the users to be simulated have been defined, the aggregator determines what percentage of demand it seeks to manage, and for this percentage of demand simulates multiple scenarios for each possible non-compliance level. In this way, it gives the system operator the different operating cost curves, and the operator makes the decision to allow or reject the amount of demand that the aggregator wishes to manage, and in the case of allowing demand management, how to deal with non-compliance.

The study that determines the suitability of demand management will give rise to multiple scenarios where the same percentages of non-compliant users generate different impacts for the system. The latter gives rise to the question of how to address non-compliance. Although the demand management scheme considered in this study has a significant voluntary component, non-compliance can be addressed through incentives to users.

5.2. How to deal with non-compliance

Despite the fact that for low levels of non-compliance demand management is still convenient, the results also show that non-compliance in demand management reduces its benefits. Given that the objective is that the savings gap is as close as possible to its expected value without considering non-compliance, it is necessary to study how to deal with non-compliance. The way to deal with this issue will depend on each system operator and/or demand aggregator. In this section we introduce the aspects to be considered for scenarios in which there is non-compliance.

An example of this savings reduction is shown in Figure 5.1. In this curve the distance between the cost curve without demand management and the cost curve considering demand management with non-compliance corresponds to the perceived savings considering non-compliance. For each percentage there will be a different savings gap which is represented by the blue area, indicating that in these cases costs are still being reduced. On the other hand, when non-compliance reaches values close to 70 %, demand management is no longer convenient and we enter to the red area, where the savings gap becomes negative. The latter scenarios are the ones to be avoided.

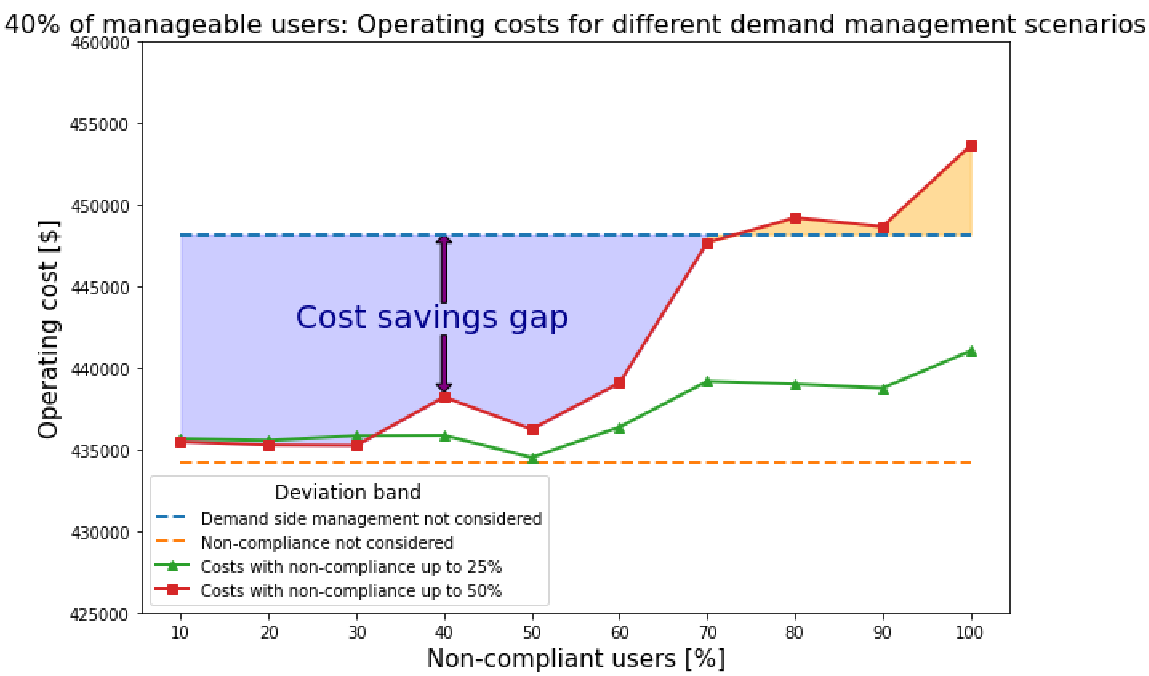


Figure 5.1: Cost saving gaps in presence of non-compliance

Below we show numerically the impact of non-compliance in the example with 40 % of non-compliant users:

$$\begin{aligned} \text{expected cost savings} &= \$448188 - \$434251 = \$13937 \\ \text{real cost savings} &= \$448188 - \$438220 = \$9968 \\ \text{cost savings difference} &= \$13937 - \$9968 = \$3969 \end{aligned} \tag{5.1}$$

The example shows how non-compliance can affect the benefits provided by demand management. Although demand management is still beneficial, for this scenario there are $3969 that are not saved, which is divided between the system operator, the demand aggregator and the users. This missing money affects the demand aggregator by not fulfilling what was agreed with the system operator. The latter begs the question, what can we do with this missing money?

Since the revenue model may be different for each aggregator, three approaches are considered that are compatible with the case study, where the expected savings must be divided between the operator, the aggregator and the users:

- Pass the cost onto the users: Given that, at the time of operation, the managed demand does not behave as expected due to non-compliance from the users, each user must take responsibility for not fulfilling what was promised to the aggregator.

  In the example, the missed savings are $3969, considering the aforementioned way of dealing with non-compliance, this amount is recovered from the benefits received by the users for the non-compliance management. This charge is divided among all users who exceeded the non-compliance allowed by the aggregator and should appropriately be in proportion to the revenue the user receives from demand management, and the magnitude of the non-compliance.

  It is important to note that if demand management is voluntary, the user must be given the freedom to deviate from their expected consumption. For this reason, in these cases the demand aggregator must define a margin of deviation allowed in the consumption of users.

- Establish a margin of error in demand management compliance: The high variability of human behavior makes it difficult for all managed users to meet the promised consumption profile. Taking this into account, a good solution to non-compliance is to anticipate its occurrence.

  If the aggregator assumes that there will be a percentage of demand whose behavior will not be as expected, it will be able to define a margin of error that will be given to the system operator. The operator will decide how to incorporate this margin of error in the operation and planning of the system (make a more robust dispatch, incorporate the stochastic nature of human behavior, or other). By defining this margin of error, a reduction in the revenues of the aggregator and the users is expected by reducing the expected savings gap to be shared. As a counterpart to the reduction in revenues, the impact of non-compliance is thus divided between the aggregator and the managed users and allows greater flexibility in demand management.

- Define revenues retrospectively: To avoid having expected savings that are not met, there is the alternative of not defining an expected savings from demand management, and divide the revenues from demand management retrospectively.

  In the above example, the expected cost difference would not have been calculated.

On the other hand, the demand aggregator would not have been able to determine the revenues that would be generated for himself and the users from demand management.

5.2.1. Different ω_2 deviation bands

In addition to the percentage of non-compliance, it should also be noted the difference on the impact that occurs for different bands of deviation from the ω_2 value in the users. For the same percentage of non-compliant users, the impact on the system may be different for different deviations in the importance that users give to their welfare. This difference in the impact on operating costs may even mean that for a given percentage of non-compliance, management is convenient for one band and not for the other.

Figure 5.2 shows the difference in savings for different ω_2 deviation bands. In the graph, the difference in savings obtained with demand management corresponds to the difference between the red curve and the green curve for each non-compliance percentage. From this example it is evident that there are deviation bands that the system is capable to allow without making demand management no longer convenient.

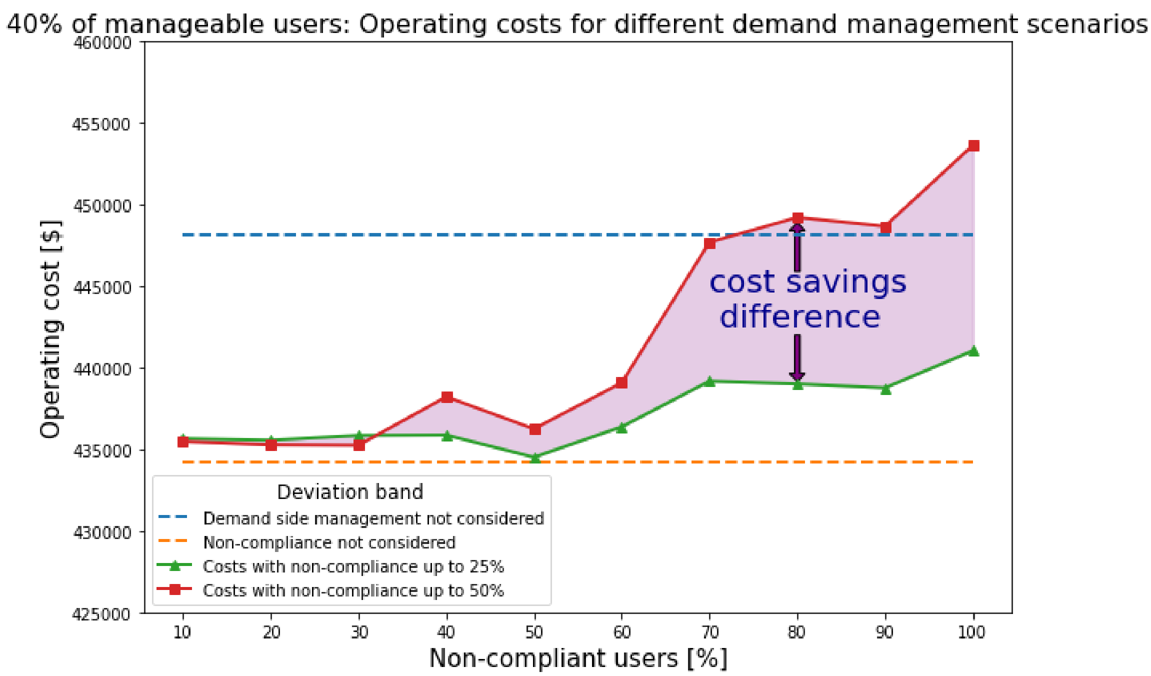


Figure 5.2: Cost saving gaps difference for differents ω_2 deviation bands.

The example shown in the figure reveals that for a 50 % deviation band (high consumption deviation) there are scenarios in which demand management implies an increase in system operating costs with respect to the case without demand management. On the other hand, for the 25 % deviation band (small consumption deviation), demand management is always convenient. In practice this information could be very valuable for the demand aggregator implementing demand management.

With the information of which bands are critical to the system, the aggregator can set the non-compliance limits that it allows to users participating in demand management. In this case, if the users deviation indicates a deviation from its ω_2 value close to 50 %, then this deviation must be penalized since at a massive level it generates a significant impact. Through this penalty, the number of users whose non-compliance reaches critical values is reduced, avoiding falling into critical scenarios.

On the other hand, based on the curves, the aggregator can decide that changes in the consumption profile equivalent to a deviation of 25 % of the ω_2 value indicated by the user is allowed without any type of penalty. Deviating the consumption curve considering this deviation band is allowed because even if there are a large number of non-compliant users, demand management will always be convenient. However, any deviation band generates a reduction in the savings obtained, so although a degree of flexibility may be allowed, the deviation should be encouraged to be as close to 0 as possible.

5.3. Enerdis

One of the main motivations for the topic addressed in the study of this thesis is the validation that it could provide to the demand management scheme that Enerdis seeks to implement. The implications that the results have for the entrepreneurship are discussed below. Within the analysis, the differences in the ω_2 deviation bands and the non-compliance percentages are considered.

The results obtained allow for the validation of the demand-side management scheme that Enerdis seeks to implement. Given that for low non-compliance percentages demand management continues generating savings for the system, it is possible to implement a DR program with a voluntary component on the part of the users. The inclusion of this DR program will bring benefits to the system, to Enerdis and to the users.

Given that even with non-compliance economic benefits are generated, it is expected that these benefits can be passed on to customers. The transfer of benefits is intended to be delivered periodically, for example every 1 month, rewarding users who comply with their consumption promise, and penalizing those who deviated more than allowed. By having this economic incentive it is possible to motivate users to adjust as much as possible to the demand profile they promised.

Since deviation will have a negative impact on the users benefits, this will motivate users to be more transparent about their consumption promise, which will result in not making consumption promises that cannot be fulfilled. The latter benefits the aggregator by having more reliable users and avoiding a bad use of the demand promises to the aggregator, such as a boycott to the electric system. Despite this, it must be considered that there will be unreliable users, which must be addressed.

It is important to note that currently it is not possible to reward customers with money as the figure of the demand aggregator is not part of the electricity market. However, this is being discussed in the country and it is expected that soon the figure of the demand aggregator will be part of the market. When this happens, and when Enerdis grows, it will be feasible to implement the economic incentive proposed above.

5.3.1. Deviations of ω_2

The obtained results show the importance of the magnitude of the deviation in the demand profile. A study such as the one presented in this thesis can be useful to determine how much deviation Enerdis can allow within its user base. Considering that the scheme considers the voluntary participation of the users, flexibility will be allowed when they make consumption promises, i.e., a deviation in their consumption equivalent to a certain ω_2 deviation will be allowed.

Using the case study scenarios with 40 % managed demand as an example, we note that an ω_2 deviation band of 25 % generates a considerably lower impact than a deviation of up to 50 %. Taking this into consideration, and seeing that the 25 % band does not exceed the cost threshold without demand management, it is decided to allow changes in the consumption profile equivalent to a 25 % deviation from the ω_2 value defined by the user. On the other hand, changes in the demand profile equivalent to a 50 % deviation from the ω_2 value are penalized.

On the other hand, from previous demand profiles Enerdis can determine how reliable are the users whose demand is managed. From this number, the expected non-compliance percentage can be established from the reliability of the users. Knowing the number of unreliable users, and the critical deviation band of ω_2, the margin of error of the savings to be obtained with demand management can be estimated.

Figure 5.3 shows the margin of error for the case analyzed, considering, as an example, that there are 60 % of unreliable users. To define this margin of error, the cost curve for the maximum allowable deviation (which in this example is 25 %) was used. The operating cost for a non-compliance percentage equal to the number of unreliable users, which in this case is 60 %, was located on this curve. Once the point that fulfills the above was found, the margin of error used was the difference between the expected cost without non-compliance, and the maximum operating cost with up to 60 % of non-compliant users, as shown in equation 5.2.

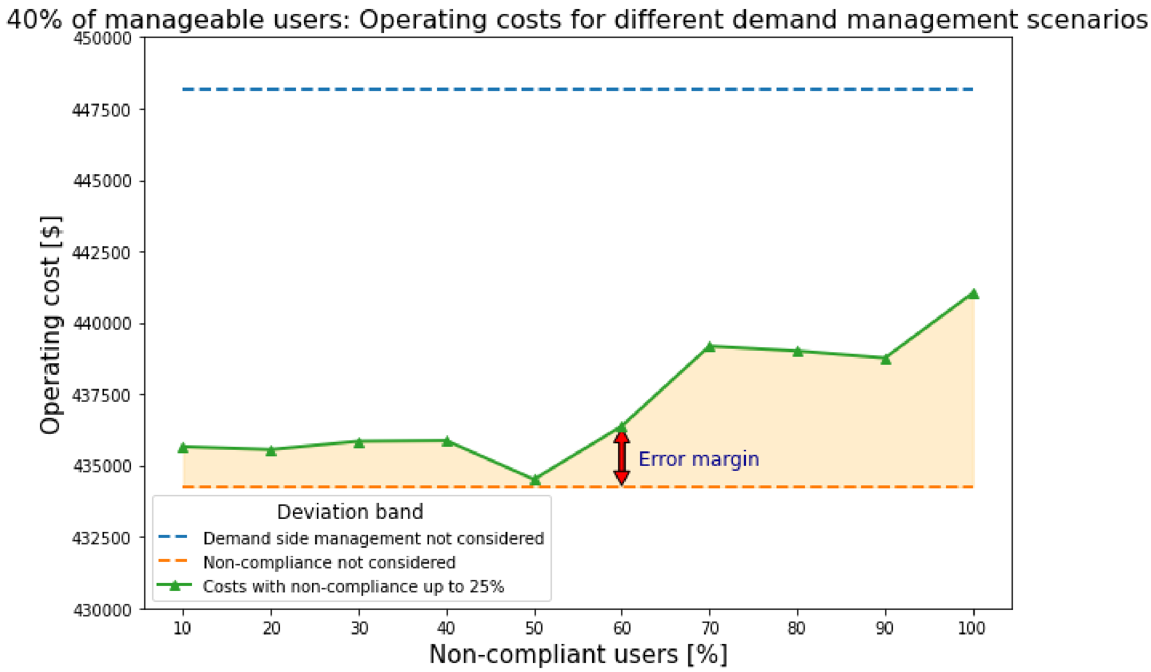


Figure 5.3: Error margin example.

$$\text{Error margin} = max\{\$435660, \$435559, \$435852, \$435874, \$434513, \$436383\} - \$434251 \tag{5.2}$$

$$\text{Error margin} = \$436383 - \$43425 \tag{5.3}$$

$$\text{Error margin} = \$2132 \tag{5.4}$$

Considering this margin of error, it is possible to anticipate non-compliance and provide this information to be considered in the operation of the system, in order to minimize the use of emergency generators for scenarios in which non-compliance is high. By considering this margin of error, the expected savings decrease in exchange for greater flexibility, so that Enerdis, users and the system operator receive a lower economic benefit from demand management. However, the risk of using emergency generators that could be more costly to the system is reduced. It is important to note that how the margin of error is incorporated into the operation of the system depends on the operator, which is beyond the scope of Enerdis.

From the above example, it is observed that it is necessary to classify the reliability of the users participating in the demand management. For this purpose, it is also useful to use the equivalent deviation band of ω_2 based on the deviations in the promised demand profile. For this, the historical behavior of the user should be reviewed, and based on the identified deviations, it should be determined whether the user is reliable. To determine the users reliability it is necessary to establish a threshold of the users consumption deviation. In the example a suitable threshold is 25 %, since it is known that for at least this percentage non-compliance does not lead the system to critical scenarios. Thus, if it is determined that the non-compliance of a user has been greater than 25 % since the start of demand management, this user is classified as an unreliable user, otherwise, it is considered a reliable user.

The above case can be generalized to other systems, where the critical ω_2 deviation band has different values. Therefore, the threshold for determining the reliability of a user will be different for each system, depending on the impact that the deviation will have on the consumption profile of the users.

Finally, it is important to note that although the demand-side management that Enerdis seeks to implement benefits the system and users, it would also have negative effects if implemented. The main affected would be the generators whose machines are not being used due to their high operating costs and/or their high emissions factor. By massively encouraging users to consume at times when renewable generation is maximized or away from peak hours, it will result in a low use of machines that expected to have a greater participation in the dispatch when they were incorporated to the system. This will have an impact on the revenues of the generators and could generate inconveniences from what they have established in their contracts with consumers.

Chapter 6

Conclusion

In this thesis, the impact of non-compliance with demand management programs is studied. The main outcome of the thesis confirms the hypothesis, this is, that demand management considering voluntary participation schemes is economically convenient even when considering non-compliance by users. From the results it is shown that when the deviation in users consumption is small (about 25 % deviation of ω_2), demand management continues to generate savings in the system regardless of how many users deviate, since the economic impact generated by non-compliance is less than the benefit generated by demand management, generating a cost overrun of less than 1.5 % in the system. On the other hand, when the deviation in user consumption is greater (about 50 % deviation of ω_2), a threshold of number of users in non-compliance appears. At this threshold the demand management may no longer be convenient since cost overruns can reach values close to 5 % (mainly due to the use of emergency generators, supplying more than 100 [MWh] in the most critical cases), exceeding the savings provided by demand management. The above mentioned threshold in the case study is close to 60 % of the users and for greater quantities it cannot be guaranteed that demand management is convenient. Demand management convenience cannot be guaranteed when the above threshold is exceeded because in such a case the large economic impact on the system is likely to be greater than the economic benefit of demand management.

The main conclusion from the results is, from the above, that a demand aggregator can allow, although it will never be desired, that all users slightly deviate their ω_2 value (which will also depend on the level of electrification of the users), in the case study, such low deviation corresponds to 25 % of their ω_2 value. On the other hand, to avoid economic impacts on the operation of the grid, larger deviations should be penalized, in the case of the study, deviations of ω_2 greater than 50 % should be penalized. From this, it is concluded that for a demand aggregator that considers voluntary participation of users, as Enerdis seeks to be, it must allow for a maximum non-compliance equivalent to a certain ω_2 deviation to give flexibility to users, but minimizing the risks of having economic impacts on the system.

To carry out the experiments, two different systems were studied for different demand management scenarios, using models for the creation of users and their preferences. The results obtained showed that non-compliance, in the vast majority of the scenarios, means an increase in the system operating costs generating and economic impact on the system. This was caused by an operation that is not optimal given the real demand with which it works, but is optimal for an expected demand that differs in practice. Despite this suboptimal result and its associated economic impact, demand management remained desirable in most of the studied scenarios. Another important finding of the results is the large number of scenarios where emergency generators must be used, being this one of the main factor that generates an increase in operating costs due to non-compliance in management.

6.1. Future Work

As part of the future work, the most relevant aspect that has been identified is the development of a model that allows estimating the probability that a user does not comply with the consumption defined from the demand management program. Once the probability of non-compliance is defined, it must be determined the magnitude of this deviation in the importance given to the user's welfare over the price signal.

The construction of the mentioned model involves interdisciplinary work, since in addition to defining the electrical aspects of the model such as the consumption of the different appliances, or the presence of distributed resources such as solar generation or storage systems, sociological aspects related to human behavior and how it will respond to the price signal must also be considered. Other variables such as the socioeconomic situation of the user under study, the members of the household, the time of day, their previous behavior in demand management, among others, must also be taken into account.

The construction of the model that allows estimating or predicting non-compliance in demand management will also depend on the type of user of the system in which the work is done. Therefore, as part of the future work, a study of the impact of non-compliance in demand management for the Chilean case is also highlighted. For this purpose, the Chilean electricity system should be used, where, in addition to the development of the non-compliance model in demand management, the CREST model of user creation should also be adjusted. It is important to note that an eventual adjustment of the CREST model does not modify the above conclusions even though it modifies the statistics used for the creation of users.

The CREST model was built based on information from users in the United Kingdom, so in the case of a study for the Chilean electricity system, the model must be adjusted according to the preferences and characteristics of a consumer in Chile. These characteristics are expected to be different from those of a user in the United Kingdom in aspects such as the probability of presence of certain appliances in homes, comfort temperatures, among others. With this new user creation model for the Chilean case, is possible to study more deeply the impact that non-compliance in demand management can have on the Chilean electricity system.

On the other hand, based on the identified impacts caused by non-compliance, is important to determine how to mitigate the effects of non-compliance on demand management as economically as possible, without compromising the security of the system considering the proposals on how to deal with non-compliance.

Linked to the mitigation of non-compliance in demand management, the inclusion of VoLL in the analysis also stands out. The inclusion of VoLL will generate modifications on the system's operating cost overruns and may significantly affect the number of scenarios where demand management given a certain level of non-compliance is not convenient. This because the high cost that loss of load may have in comparison with the system's generators, including emergency generators.

Bibliography

[1] P. Manoj, Y. B. Kumar, M. Gowtham, D. Vishwas, and A. Ajay, "Chapter 6 - internet of things for smart grid applications," in *Advances in Smart Grid Power System* (A. Tomar and R. Kandari, eds.), pp. 159–190, Academic Press, 2021.

[2] G. Gaur, N. Mehta, R. Khanna, and S. Kaur, "Demand side management in a smart grid environment," in *2017 IEEE International Conference on Smart Grid and Smart Cities (ICSGSC)*, pp. 227–231, 2017.

[3] R. Sharifi, S. Fathi, and V. Vahidinasab, "A review on demand-side tools in electricity market," *Renewable and Sustainable Energy Reviews*, vol. 72, pp. 565–572, 2017.

[4] C. V. Chandran, M. Basu, and K. Sunderland, "Demand response and consumer inconvenience," in *2019 International Conference on Smart Energy Systems and Technologies (SEST)*, pp. 1–6, 2019.

[5] L. Gao and L. Ma, "A pricing method for demand response using game theory," in *2021 3rd Asia Energy and Electrical Engineering Symposium (AEEES)*, pp. 1024–1029, 2021.

[6] Y. Liu, L. Xiao, G. Yao, and S. Bu, "Pricing-based demand response for a smart home with various types of household appliances considering customer satisfaction," *IEEE Access*, vol. 7, pp. 86463–86472, 2019.

[7] E. McKenna and M. Thomson, "High-resolution stochastic integrated thermal–electrical domestic demand model," *Applied Energy*, vol. 165, pp. 445–461, 2016.

[8] P. Samadi, A.-H. Mohsenian-Rad, R. Schober, V. W. S. Wong, and J. Jatskevich, "Optimal real-time pricing algorithm based on utility maximization for smart grid," in *2010 First IEEE International Conference on Smart Grid Communications*, pp. 415–420, 2010.

[9] J.-Y. Joo and M. D. Ilić, "A multi-layered adaptive load management (alm) system: Information exchange between market participants for efficient and reliable energy use," in *IEEE PES T D 2010*, pp. 1–7, 2010.

[10] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart grid — the new and improved power grid: A survey," *IEEE Communications Surveys Tutorials*, vol. 14, no. 4, pp. 944–980, 2012.

[11] M. Shabanzadeh and M. Moghaddam, "What is the smart grid? definitions, perspectives, and ultimate goals," in *Power System Conference*, 2013.

[12] F. Saffre and R. Gedge, "Demand-side management for the smart grid," in *2010 IEEE/IFIP Network Operations and Management Symposium Workshops*, pp. 300–303, 2010.

[13] Coordinador Eléctrico Nacional, "Operación: Demanda programada," 2021. Availa-

ble in https://www.coordinador.cl/operacion/graficos/demanda/demanda-programada-demanda/ on July, 2021.

[14] K. P. Swain and M. De, "Analysis of effectiveness of flexible load shifting order on optimum dsm," in *2017 IEEE International WIE Conference on Electrical and Computer Engineering (WIECON-ECE)*, pp. 141–144, 2017.

[15] R. Sharifi, S. H. Fathi, A. Anvari-Moghaddam, J. M. Guerrero, and V. Vahidinasab, "An economic customer-oriented demand response model in electricity markets," in *2018 IEEE International Conference on Industrial Technology (ICIT)*, pp. 1149–1153, 2018.

[16] P. Corsi, P. Faria, and Z. Vale, "Elasticity parameter definition and analysis for real-time pricing remuneration basing on different users cases," in *2019 International Conference on Smart Energy Systems and Technologies (SEST)*, pp. 1–6, 2019.

[17] S. Davarzani, I. Pisica, and G. A. Taylor, "Assessment of residential electricity tariff switching based on customer response elasticity," in *2017 52nd International Universities Power Engineering Conference (UPEC)*, pp. 1–6, 2017.

[18] Enel X, "What is demand side management?," 2021. Available at https://corporate.enelx.com/en/question-and-answers/what-is-demand-side-management on July, 2021.

[19] O. Elma and U. S. Selamoğullar, "A survey of a residential load profile for demand side management systems," in *2017 IEEE International Conference on Smart Energy Grid Engineering (SEGE)*, pp. 85–89, 2017.

[20] S. Gyamfi, S. Krumdieck, and T. Urmee, "Residential peak electricity demand response—highlights of some behavioural issues," *Renewable and Sustainable Energy Reviews*, vol. 25, pp. 71–77, 2013.

[21] S. Mohajeryami, M. Doostan, A. Asadinejad, and P. Schwarz, "Error analysis of customer baseline load (cbl) calculation methods for residential customers," *IEEE Transactions on Industry Applications*, vol. 53, no. 1, pp. 5–14, 2017.

[22] L. Lutzenhiser, "Social and behavioral aspects of energy use," *Annual Review of Energy and the Environment*, vol. 18, no. 1, pp. 247–289, 1993.

[23] P. C. Reiss and M. W. White, "Household Electricity Demand, Revisited," *The Review of Economic Studies*, vol. 72, pp. 853–883, 07 2005.

[24] M. Alizadeh, M. Parsa Moghaddam, N. Amjady, P. Siano, and M. Sheikh-El-Eslami, "Flexibility in future power systems with high renewable penetration: A review," *Renewable and Sustainable Energy Reviews*, vol. 57, pp. 1186–1193, 2016.

[25] Centro de Energía, "Prospection in energy digitization," 2020. Available at https://www.energypartnership.cl/fileadmin/user_upload/chile/media_elements/Studies/CHL_20201130_Prospection_in_Energy_Digitalization_in_Chile_01.pdf on July, 2021.

[26] H. Sui, Y. Sun, and W.-J. Lee, "A demand side management model based on advanced metering infrastructure," in *2011 4th International Conference on Electric Utility Deregulation and Restructuring and Power Technologies (DRPT)*, pp. 1586–1589, 2011.

[27] P. Wang, J. Y. Huang, Y. Ding, P. Loh, and L. Goel, "Demand side load management of smart grids using intelligent trading/metering/ billing system," in *2011 IEEE Trondheim*

PowerTech, pp. 1–6, 2011.

[28] I. B. Dhaou, "Smart plug design for demand side management program," in *2019 4th International Conference on Power Electronics and their Applications (ICPEA)*, pp. 1–5, 2019.

[29] V. Caballero, D. Vernet, and A. Zaballos, "Social internet of energy—a new paradigm for demand side management," *IEEE Internet of Things Journal*, vol. 6, no. 6, pp. 9853–9867, 2019.

[30] V. Reddy, M. Rabbani, M. T. Arif, and A. M. Oo, "Iot for energy efficiency and demand management," in *2019 29th Australasian Universities Power Engineering Conference (AUPEC)*, pp. 1–6, 2019.

[31] A. Obushevs, I. Oleinikova, and A. Mutule, "Demand side management platform for han flexibility estimation with agent control," in *2016 13th International Conference on the European Energy Market (EEM)*, pp. 1–5, 2016.

[32] R. Gore and M. Kande, "Analysis of wide area monitoring system architectures," in *2015 IEEE International Conference on Industrial Technology (ICIT)*, pp. 1269–1274, 2015.

[33] IEEE Standards Association, "Ieee standard for smart energy profile application protocol," 2018. Available at https://standards.ieee.org/standard/2030_5-2018.html on July, 2021.

[34] OpenADR Alliance, "Open adr alliance home page," 2020. Available at https://www.openadr.org/about-us on July, 2021.

[35] OpenADR Alliance, "Open adr frequently asked questions," 2020. Available at https://www.openadr.org/faq on July, 2021.

[36] F. Seitenfus, C. H. Barriquello, L. Neves Canha, A. Pedretti, T. A. Silva Santana, and Z. Nadal, "Simulation and analysis of openadr agents using volttron platform," in *2019 IEEE PES Innovative Smart Grid Technologies Conference - Latin America (ISGT Latin America)*, pp. 1–6, 2019.

[37] U. Herberg, D. Mashima, J. G. Jetcheva, and S. Mirzazad-Barijough, "Openadr 2.0 deployment architectures: Options and implications," in *2014 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pp. 782–787, 2014.

[38] Z. Jingxi, C. Min, W. Ling, Y. Lixia, P. Shixiong, and L. Dong, "Research on architecture of automatic demand response system based on openadr," in *2018 China International Conference on Electricity Distribution (CICED)*, pp. 2984–2988, 2018.

[39] OpenADR Alliance, "The open adr primer: An introduction to automated demand response and the open adr standard," 2020. Available at https://www.openadr.org/assets/docs/openadr_primer.pdf on July, 2021.

[40] R. Ghatikar and R. Bienert, "Smart grid standards and systems interoperability: A precedent with openadr," in *Grid-Interop 2011*, 2011.

[41] M. Taylor, "Climate crisis seen as "most important issue" by public, poll shows," *The Guardian*, vol. 18, pp. 09–19, 2019.

[42] A. Naeem, A. Shabbir, N. Ul Hassan, C. Yuen, A. Ahmad, and W. Tushar, "Understanding customer behavior in multi-tier demand response management program," *IEEE*

Access, vol. 3, pp. 2613–2625, 2015.

[43] L. Ma, N. Han, S. Chen, and T. Gao, "A study of day-ahead scheduling strategy of demand response for resident flexible load in smart grid," in *2020 Management Science Informatization and Economic Innovation Development Conference (MSIEID)*, pp. 197–200, 2020.

[44] W. Brokering Christie, R. Palma Behnke, *Atrapando el sol en los Sistemas Eléctricos de Potencia*. 2018. Available at http://sepsolar.centroenergia.cl/pdf/libro_download.pdf on July, 2021.

[45] F. Staff, "Economic dispatch: Concepts, practices and issues," *Palm Springs California, 11*, 2005.

[46] N. Padhy, "Unit commitment-a bibliographical survey," *IEEE Transactions on Power Systems*, vol. 19, no. 2, pp. 1196–1205, 2004.

[47] M. Govardhan and R. Roy, "Impact of demand side management on unit commitment problem," in *Proceedings of The 2014 International Conference on Control, Instrumentation, Energy and Communication (CIEC)*, pp. 446–450, 2014.

[48] M. Nikzad and S. S. S. Farahani, "Studying emergency demand response programs based on exponential modeling in smart grids," in *2012 International Conference on Renewable Energies for Developing Countries (REDEC)*, pp. 1–6, 2012.

[49] V. K. Tumuluru, Z. Huang, and D. H. K. Tsang, "Integrating price responsive demand into the unit commitment problem," *IEEE Transactions on Smart Grid*, vol. 5, no. 6, pp. 2757–2765, 2014.

[50] B. Gwisdorf, S. Stepanescu, and C. Rehtanz, "Effects of demand side management on the planning and operation of distribution grids," in *2010 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT Europe)*, pp. 1–5, 2010.

[51] C. Spataru and P. Bouffaron, "Chapter 22 - off-grid energy storage," in *Storing Energy* (T. M. Letcher, ed.), pp. 477–497, Oxford: Elsevier, 2016.

[52] M. R. Tur, S. Ay, A. Erduman, A. Shobole, and M. Wadi, "Impact of demand side management on spinning reserve requirements designation," *International Journal of Renewable Energy Research*, vol. 7, pp. 946–953, 01 2017.

[53] D. Contreras Jara, "Propuesta metodológica para dimensionar y evaluar, técnica y económicamente, micro-redes urbanas," 2020. Available at https://repositorio.uchile.cl/bitstream/handle/2250/177345/Propuesta-metodologica-para-dimensionar-y-evaluar-tecnica-y-economicamente-micro-redes-urbanas.pdf?sequence=1&isAllowed=y on July, 2021.

[54] S. Rafiei and A. Bakhshai, "A review on energy efficiency optimization in smart grid," in *IECON 2012 - 38th Annual Conference on IEEE Industrial Electronics Society*, pp. 5916–5919, 2012.

[55] M. F. Akorede, H. Hizam, and E. Pouresmaeil, "Distributed energy resources and benefits to the environment," *Renewable and Sustainable Energy Reviews*, vol. 14, no. 2, pp. 724–734, 2010.

[56] A. Poullikkas, "A comparative assessment of net metering and feed in tariff schemes

for residential pv systems," *Sustainable Energy Technologies and Assessments*, vol. 3, pp. 1–8, 2013.

[57] M. Pérez Seguel, "Electrificaicón del uso del calor residencial proyecciones en chile y su rol en la gestión de demanda," 2021. Available at https://repositorio.uchile.cl/bitstream/handle/2250/182351/Electrificacion-del-uso-de-calor-residencial-proyecciones-en-Chile.pdf?sequence=1&isAllowed=y on April, 2022.

[58] G. Di Leo, M. Landi, V. Paciello, and A. Pietrosanto, "Smart metering for demand side management," in *2012 IEEE International Instrumentation and Measurement Technology Conference Proceedings*, pp. 1798–1803, 2012.

[59] S. F. Railsback and V. Grimm, *Agent-based and individual-based modeling: a practical introduction*. Princeton university press, 2019.

[60] Coordinador Eléctrico Nacional, "Operación programada," 2017. Available at https://sic.coordinador.cl/informes-y-documentos/fichas/operacion-programada-2/ on July, 2021.

[61] N. Gebrie Yáñez, "Gestión de la demanda a través de las cargas refrigerantes, para la operación económica de los sistemas eléctricos de potencia," 2018. Available at https://repositorio.uchile.cl/bitstream/handle/2250/169248/Gesti%c3%b3n-de-la-demanda-a-trav%c3%a9s-de-las-cargas-refrigerantes-para-la-operaci%c3%b3n-econ%c3%b3mica-de-los-sistemas.pdf?sequence=1&isAllowed=y on July, 2021.

[62] Coordinador Eléctrico Nacional, "Información de instalaciones," 2021. Available at https://infotecnica.coordinador.cl/instalaciones/?eid=0&type=43 on July, 2021.

[63] Comisión Nacional de Energía, "Estudio costo de falla de corta y larga duración sen y ssmm," 2021. Available at https://www.cne.cl/wp-content/uploads/2021/07/Res.Exta_.N%C2%B0234-Aprueba-ITF-Estudio-de-Costos-de-Falla-21.07.21.pdf on July,2021.

[64] Comisión Nacional de Energía, "Informe de costos de tecnologÍas de generación," 2020. Available at https://www.cne.cl/wp-content/uploads/2020/03/ICTG-Marzo-2020.pdf on July, 2021.

[65] Ministerio de Energía, "Explorador solar," 2021. Available at http://solar.minenergia.cl/ on July, 2021.

[66] Ministerio de Energía, "Explorador eólico," 2021. Available at https://eolico.minenergia.cl/ on July, 2021.

[67] Coordinador Eléctrico Nacional, "Costo marginal programado," 2021. Available at https://www.coordinador.cl/mercados/graficos/costos-marginales/costo-marginal-programado/ on July, 2021.

[68] O. Holub and M. Sikora, "End user models for residential demand response," in *IEEE PES ISGT Europe 2013*, pp. 1–4, 2013.

Annexes A

Results

Table A.1: Case study of 24 buses mix 1: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
1	1/25	0/25	0 %	407,946.78	407,946.78
2	1/25	1/25	25 %	407,946.78	409,601.92
3	1/25	1/25	50 %	407,946.78	410,151.39
4	2/25	0/25	0 %	405,971.13	405,971.13
5	2/25	1/25	25 %	405,971.13	407,561.88
6	2/25	2/25	25 %	405,971.13	407,569.82
7	2/25	1/25	50 %	405,971.13	407,949.26
8	2/25	2/25	50 %	405,971.13	409,207.13
9	3/25	0/25	0 %	393,786.36	393,786.36
10	3/25	1/25	25 %	393,786.36	395,454.67
11	3/25	2/25	25 %	393,786.36	395,680.90
12	3/25	3/25	25 %	393,786.36	395,330.26
13	3/25	1/25	50 %	393,786.36	395,505.79
14	3/25	2/25	50 %	393,786.36	395,687.74
15	3/25	3/25	50 %	393,786.36	396,708.09
16	4/25	0/25	0 %	398,357.92	398,357.92
17	4/25	1/25	25 %	398,357.92	399,982.22
18	4/25	2/25	25 %	398,357.92	399,960.98
19	4/25	3/25	25 %	398,357.92	399,592.64
20	4/25	4/25	25 %	398,357.92	401,721.55
21	4/25	1/25	50 %	398,357.92	399,888.64
22	4/25	2/25	50 %	398,357.92	399,827.92
23	4/25	3/25	50 %	398,357.92	399,234.47
24	4/25	4/25	50 %	398,357.92	403,019.89
25	5/25	0/25	0 %	397,310.30	397,310.30
26	5/25	1/25	25 %	397,310.30	399,129.24
27	5/25	2/25	25 %	397,310.30	399,095.47
28	5/25	3/25	25 %	397,310.30	398,714.68
29	5/25	4/25	25 %	397,310.30	397,667.40

Table A.1: Case study of 24 buses mix 1: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
30	5/25	5/25	25 %	397,310.30	399,753.30
31	5/25	1/25	50 %	397,310.30	398,985.25
32	5/25	2/25	50 %	397,310.30	398,714.10
33	5/25	3/25	50 %	397,310.30	398,038.36
34	5/25	4/25	50 %	397,310.30	402,108.43
35	5/25	5/25	50 %	397,310.30	405,358.44
36	6/25	0/25	0 %	408,067.92	408,067.92
37	6/25	1/25	25 %	408,067.92	410,054.19
38	6/25	2/25	25 %	408,067.92	411,702.93
39	6/25	3/25	25 %	408,067.92	408,465.52
40	6/25	4/25	25 %	408,067.92	408,171.24
41	6/25	5/25	25 %	408,067.92	408,117.80
42	6/25	6/25	25 %	408,067.92	410,598.63
43	6/25	1/25	50 %	408,067.92	410,831.77
44	6/25	2/25	50 %	408,067.92	415,268.44
45	6/25	3/25	50 %	408,067.92	416,162.05
46	6/25	4/25	50 %	408,067.92	415,390.48
47	6/25	5/25	50 %	408,067.92	414,924.68
48	6/25	6/25	50 %	408,067.92	416,989.08
49	7/25	0/25	0 %	414,488.44	414,488.44
50	7/25	1/25	25 %	414,488.44	414,510.63
51	7/25	2/25	25 %	414,488.44	415,441.28
52	7/25	3/25	25 %	414,488.44	419,735.94
53	7/25	4/25	25 %	414,488.44	416,110.38
54	7/25	5/25	25 %	414,488.44	415,848.89
55	7/25	6/25	25 %	414,488.44	415,688.77
56	7/25	7/25	25 %	414,488.44	419,435.22
57	7/25	1/25	50 %	414,488.44	413,261.65
58	7/25	2/25	50 %	414,488.44	415,734.86
59	7/25	3/25	50 %	414,488.44	417,509.46
60	7/25	4/25	50 %	414,488.44	424,582.32
61	7/25	5/25	50 %	414,488.44	423,758.61
62	7/25	6/25	50 %	414,488.44	423,055.65
63	7/25	7/25	50 %	414,488.44	428,524.15
64	8/25	0/25	0 %	417,893.12	417,893.12
65	8/25	1/25	25 %	417,893.12	418,154.12
66	8/25	2/25	25 %	417,893.12	418,176.30
67	8/25	3/25	25 %	417,893.12	417,664.81
68	8/25	4/25	25 %	417,893.12	418,768.39
69	8/25	5/25	25 %	417,893.12	418,741.20
70	8/25	6/25	25 %	417,893.12	418,547.50

Table A.1: Case study of 24 buses mix 1: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
71	8/25	7/25	25 %	417,893.12	418,319.92
72	8/25	8/25	25 %	417,893.12	421,882.99
73	8/25	1/25	50 %	417,893.12	417,951.98
74	8/25	2/25	50 %	417,893.12	416,991.38
75	8/25	3/25	50 %	417,893.12	417,154.97
76	8/25	4/25	50 %	417,893.12	421,349.49
77	8/25	5/25	50 %	417,893.12	430,967.51
78	8/25	6/25	50 %	417,893.12	430,142.19
79	8/25	7/25	50 %	417,893.12	429,697.02
80	8/25	8/25	50 %	417,893.12	431,221.48
81	9/25	0/25	0 %	425,325.00	425,325.00
82	9/25	1/25	25 %	425,325.00	425,224.39
83	9/25	2/25	25 %	425,325.00	426,284.51
84	9/25	3/25	25 %	425,325.00	426,306.70
85	9/25	4/25	25 %	425,325.00	425,141.16
86	9/25	5/25	25 %	425,325.00	426,841.19
87	9/25	6/25	25 %	425,325.00	430,601.55
88	9/25	7/25	25 %	425,325.00	430,400.89
89	9/25	8/25	25 %	425,325.00	430,184.29
90	9/25	9/25	25 %	425,325.00	433,365.58
91	9/25	1/25	50 %	425,325.00	425,100.77
92	9/25	2/25	50 %	425,325.00	425,912.76
93	9/25	3/25	50 %	425,325.00	426,623.55
94	9/25	4/25	50 %	425,325.00	424,539.77
95	9/25	5/25	50 %	425,325.00	430,742.86
96	9/25	6/25	50 %	425,325.00	442,221.54
97	9/25	7/25	50 %	425,325.00	441,357.02
98	9/25	8/25	50 %	425,325.00	440,900.54
99	9/25	9/25	50 %	425,325.00	442,001.20
100	10/25	0/25	0 %	434,251.15	434,251.15
101	10/25	1/25	25 %	434,251.15	435,659.96
102	10/25	2/25	25 %	434,251.15	435,559.35
103	10/25	3/25	25 %	434,251.15	435,851.67
104	10/25	4/25	25 %	434,251.15	435,873.85
105	10/25	5/25	25 %	434,251.15	434,512.70
106	10/25	6/25	25 %	434,251.15	436,382.86
107	10/25	7/25	25 %	434,251.15	439,180.13
108	10/25	8/25	25 %	434,251.15	439,011.47
109	10/25	9/25	25 %	434,251.15	438,765.03
110	10/25	10/25	25 %	434,251.15	441,041.48
111	10/25	1/25	50 %	434,251.15	435,477.09

Table A.1: Case study of 24 buses mix 1: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
112	10/25	2/25	50 %	434,251.15	435,275.87
113	10/25	3/25	50 %	434,251.15	435,248.50
114	10/25	4/25	50 %	434,251.15	438,220.22
115	10/25	5/25	50 %	434,251.15	436,252.56
116	10/25	6/25	50 %	434,251.15	439,081.30
117	10/25	7/25	50 %	434,251.15	447,696.24
118	10/25	8/25	50 %	434,251.15	449,216.06
119	10/25	9/25	50 %	434,251.15	448,678.45
120	10/25	10/25	50 %	434,251.15	453,634.82
121	11/25	0/25	0 %	437,273.14	437,273.14
122	11/25	1/25	25 %	437,273.14	440,505.53
123	11/25	2/25	25 %	437,273.14	442,898.89
124	11/25	3/25	25 %	437,273.14	442,798.28
125	11/25	4/25	25 %	437,273.14	442,501.24
126	11/25	5/25	25 %	437,273.14	442,523.42
127	11/25	6/25	25 %	437,273.14	438,840.09
128	11/25	7/25	25 %	437,273.14	441,478.87
129	11/25	8/25	25 %	437,273.14	442,806.95
130	11/25	9/25	25 %	437,273.14	442,632.85
131	11/25	10/25	25 %	437,273.14	443,644.69
132	11/25	11/25	25 %	437,273.14	447,269.31
133	11/25	1/25	50 %	437,273.14	440,501.53
134	11/25	2/25	50 %	437,273.14	440,658.93
135	11/25	3/25	50 %	437,273.14	440,610.71
136	11/25	4/25	50 %	437,273.14	439,730.59
137	11/25	5/25	50 %	437,273.14	442,468.14
138	11/25	6/25	50 %	437,273.14	433,930.68
139	11/25	7/25	50 %	437,273.14	439,539.95
140	11/25	8/25	50 %	437,273.14	449,393.57
141	11/25	9/25	50 %	437,273.14	448,502.61
142	11/25	10/25	50 %	437,273.14	450,529.52
143	11/25	11/25	50 %	437,273.14	459,526.58
144	12/25	0/25	0 %	439,043.46	439,043.46
145	12/25	1/25	25 %	439,043.46	440,134.24
146	12/25	2/25	25 %	439,043.46	441,099.06
147	12/25	3/25	25 %	439,043.46	441,676.52
148	12/25	4/25	25 %	439,043.46	441,575.91
149	12/25	5/25	25 %	439,043.46	440,367.90
150	12/25	6/25	25 %	439,043.46	440,390.08
151	12/25	7/25	25 %	439,043.46	438,872.38
152	12/25	8/25	25 %	439,043.46	440,351.72

Table A.1: Case study of 24 buses mix 1: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
153	12/25	9/25	25 %	439,043.46	441,636.62
154	12/25	10/25	25 %	439,043.46	441,442.04
155	12/25	11/25	25 %	439,043.46	441,213.10
156	12/25	12/25	25 %	439,043.46	444,819.83
157	12/25	1/25	50 %	439,043.46	440,046.92
158	12/25	2/25	50 %	439,043.46	441,458.60
159	12/25	3/25	50 %	439,043.46	442,829.72
160	12/25	4/25	50 %	439,043.46	442,628.50
161	12/25	5/25	50 %	439,043.46	442,195.83
162	12/25	6/25	50 %	439,043.46	441,113.42
163	12/25	7/25	50 %	439,043.46	438,734.82
164	12/25	8/25	50 %	439,043.46	444,800.81
165	12/25	9/25	50 %	439,043.46	452,457.07
166	12/25	10/25	50 %	439,043.46	451,566.11
167	12/25	11/25	50 %	439,043.46	451,022.37
168	12/25	12/25	50 %	439,043.46	455,577.83
169	13/25	0/25	0 %	443,870.94	443,870.94
170	13/25	1/25	25 %	443,870.94	442,696.41
171	13/25	2/25	25 %	443,870.94	443,607.97
172	13/25	3/25	25 %	443,870.94	444,546.61
173	13/25	4/25	25 %	443,870.94	445,217.69
174	13/25	5/25	25 %	443,870.94	445,117.08
175	13/25	6/25	25 %	443,870.94	443,909.07
176	13/25	7/25	25 %	443,870.94	443,931.25
177	13/25	8/25	25 %	443,870.94	442,490.67
178	13/25	9/25	25 %	443,870.94	443,948.32
179	13/25	10/25	25 %	443,870.94	445,540.94
180	13/25	11/25	25 %	443,870.94	445,335.86
181	13/25	12/25	25 %	443,870.94	445,117.42
182	13/25	13/25	25 %	443,870.94	447,701.01
183	13/25	1/25	50 %	443,870.94	442,696.41
184	13/25	2/25	50 %	443,870.94	443,520.65
185	13/25	3/25	50 %	443,870.94	444,906.15
186	13/25	4/25	50 %	443,870.94	445,577.40
187	13/25	5/25	50 %	443,870.94	445,376.18
188	13/25	6/25	50 %	443,870.94	444,885.17
189	13/25	7/25	50 %	443,870.94	445,185.82
190	13/25	8/25	50 %	443,870.94	442,426.00
191	13/25	9/25	50 %	443,870.94	447,398.95
192	13/25	10/25	50 %	443,870.94	457,318.41
193	13/25	11/25	50 %	443,870.94	456,155.21

Table A.1: Case study of 24 buses mix 1: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
194	13/25	12/25	50 %	443,870.94	455,600.44
195	13/25	13/25	50 %	443,870.94	461,893.99
196	14/25	0/25	0 %	443,537.13	443,537.13
197	14/25	1/25	25 %	443,537.13	443,537.13
198	14/25	2/25	25 %	443,537.13	442,350.02
199	14/25	3/25	25 %	443,537.13	445,559.35
200	14/25	4/25	25 %	443,537.13	445,905.13
201	14/25	5/25	25 %	443,537.13	446,609.85
202	14/25	6/25	25 %	443,537.13	446,509.24
203	14/25	7/25	25 %	443,537.13	445,461.79
204	14/25	8/25	25 %	443,537.13	445,483.97
205	14/25	9/25	25 %	443,537.13	443,983.66
206	14/25	10/25	25 %	443,537.13	445,706.61
207	14/25	11/25	25 %	443,537.13	446,854.90
208	14/25	12/25	25 %	443,537.13	446,675.53
209	14/25	13/25	25 %	443,537.13	446,431.37
210	14/25	14/25	25 %	443,537.13	449,416.98
211	14/25	1/25	50 %	443,537.13	446,283.90
212	14/25	2/25	50 %	443,537.13	445,110.18
213	14/25	3/25	50 %	443,537.13	448,760.84
214	14/25	4/25	50 %	443,537.13	449,388.48
215	14/25	5/25	50 %	443,537.13	452,836.23
216	14/25	6/25	50 %	443,537.13	452,482.01
217	14/25	7/25	50 %	443,537.13	451,992.73
218	14/25	8/25	50 %	443,537.13	452,087.74
219	14/25	9/25	50 %	443,537.13	448,899.33
220	14/25	10/25	50 %	443,537.13	456,524.49
221	14/25	11/25	50 %	443,537.13	466,243.47
222	14/25	12/25	50 %	443,537.13	465,352.52
223	14/25	13/25	50 %	443,537.13	464,754.87
224	14/25	14/25	50 %	443,537.13	468,526.08
225	15/25	0/25	0 %	441,682.26	441,682.26
226	15/25	1/25	25 %	441,682.26	442,057.36
227	15/25	2/25	25 %	441,682.26	442,057.36
228	15/25	3/25	25 %	441,682.26	441,172.11
229	15/25	4/25	25 %	441,682.26	441,324.00
230	15/25	5/25	25 %	441,682.26	441,402.17
231	15/25	6/25	25 %	441,682.26	445,151.56
232	15/25	7/25	25 %	441,682.26	445,067.21
233	15/25	8/25	25 %	441,682.26	444,247.35
234	15/25	9/25	25 %	441,682.26	444,269.54

Table A.1: Case study of 24 buses mix 1: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
235	15/25	10/25	25 %	441,682.26	443,027.78
236	15/25	11/25	25 %	441,682.26	442,960.42
237	15/25	12/25	25 %	441,682.26	442,240.28
238	15/25	13/25	25 %	441,682.26	442,056.13
239	15/25	14/25	25 %	441,682.26	441,756.77
240	15/25	15/25	25 %	441,682.26	442,016.40
241	15/25	1/25	50 %	441,682.26	442,044.12
242	15/25	2/25	50 %	441,682.26	441,675.92
243	15/25	3/25	50 %	441,682.26	440,845.28
244	15/25	4/25	50 %	441,682.26	440,879.88
245	15/25	5/25	50 %	441,682.26	442,961.57
246	15/25	6/25	50 %	441,682.26	443,769.75
247	15/25	7/25	50 %	441,682.26	443,568.63
248	15/25	8/25	50 %	441,682.26	442,974.90
249	15/25	9/25	50 %	441,682.26	442,936.58
250	15/25	10/25	50 %	441,682.26	438,861.37
251	15/25	11/25	50 %	441,682.26	441,165.27
252	15/25	12/25	50 %	441,682.26	442,927.50
253	15/25	13/25	50 %	441,682.26	442,190.44
254	15/25	14/25	50 %	441,682.26	445,427.18
255	15/25	15/25	50 %	441,682.26	447,582.65

Table A.2: 24-bus case study mix 2: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
1	3/25	0/25	0 %	354,462.96	354,462.96
2	3/25	1/25	25 %	354,462.96	358,577.06
3	3/25	2/25	25 %	354,462.96	358,377.47
4	3/25	3/25	25 %	354,462.96	358,159.44
5	3/25	1/25	50 %	354,462.96	360,028.52
6	3/25	2/25	50 %	354,462.96	360,245.53
7	3/25	3/25	50 %	354,462.96	361,249.29
8	7/25	0/25	0 %	373,150.38	373,150.38
9	7/25	1/25	25 %	373,150.38	373,169.34
10	7/25	2/25	25 %	373,150.38	373,539.51
11	7/25	3/25	25 %	373,150.38	374,514.52
12	7/25	4/25	25 %	373,150.38	373,556.46
13	7/25	5/25	25 %	373,150.38	373,225.38
14	7/25	6/25	25 %	373,150.38	372,955.22
15	7/25	7/25	25 %	373,150.38	376,066.72
16	7/25	1/25	50 %	373,150.38	372,415.69

Table A.2: 24-bus case study mix 2: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
17	7/25	2/25	50 %	373,150.38	373,572.63
18	7/25	3/25	50 %	373,150.38	377,273.30
19	7/25	4/25	50 %	373,150.38	384,706.35
20	7/25	5/25	50 %	373,150.38	383,950.97
21	7/25	6/25	50 %	373,150.38	383,753.24
22	7/25	7/25	50 %	373,150.38	390,596.88
23	10/25	0/25	0 %	391,611.33	391,611.33
24	10/25	1/25	25 %	391,611.33	397,959.73
25	10/25	2/25	25 %	391,611.33	397,868.68
26	10/25	3/25	25 %	391,611.33	398,311.78
27	10/25	4/25	25 %	391,611.33	398,330.73
28	10/25	5/25	25 %	391,611.33	396,619.07
29	10/25	6/25	25 %	391,611.33	397,597.83
30	10/25	7/25	25 %	391,611.33	401,141.84
31	10/25	8/25	25 %	391,611.33	400,847.56
32	10/25	9/25	25 %	391,611.33	400,568.20
33	10/25	10/25	25 %	391,611.33	405,708.15
34	10/25	1/25	50 %	391,611.33	400,806.82
35	10/25	2/25	50 %	391,611.33	400,599.02
36	10/25	3/25	50 %	391,611.33	400,429.05
37	10/25	4/25	50 %	391,611.33	405,438.75
38	10/25	5/25	50 %	391,611.33	400,923.08
39	10/25	6/25	50 %	391,611.33	404,149.18
40	10/25	7/25	50 %	391,611.33	414,531.48
41	10/25	8/25	50 %	391,611.33	416,102.50
42	10/25	9/25	50 %	391,611.33	419,932.43
43	10/25	10/25	50 %	391,611.33	429,957.08
44	14/25	0/25	0 %	402,298.14	402,298.14
45	14/25	1/25	25 %	402,298.14	403,215.61
46	14/25	2/25	25 %	402,298.14	402,922.34
47	14/25	3/25	25 %	402,298.14	402,495.01
48	14/25	4/25	25 %	402,298.14	408,334.31
49	14/25	5/25	25 %	402,298.14	411,204.45
50	14/25	6/25	25 %	402,298.14	409,691.50
51	14/25	7/25	25 %	402,298.14	409,710.46
52	14/25	8/25	25 %	402,298.14	410,077.66
53	14/25	9/25	25 %	402,298.14	409,993.58
54	14/25	10/25	25 %	402,298.14	414,215.87
55	14/25	11/25	25 %	402,298.14	408,124.26
56	14/25	12/25	25 %	402,298.14	406,229.31
57	14/25	13/25	25 %	402,298.14	407,034.78

Table A.2: 24-bus case study mix 2: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
58	14/25	14/25	25 %	402,298.14	407,034.78
59	14/25	1/25	50 %	402,298.14	403,039.34
60	14/25	2/25	50 %	402,298.14	405,504.57
61	14/25	3/25	50 %	402,298.14	408,802.63
62	14/25	4/25	50 %	402,298.14	416,035.22
63	14/25	5/25	50 %	402,298.14	417,604.87
64	14/25	6/25	50 %	402,298.14	419,137.13
65	14/25	7/25	50 %	402,298.14	423,986.91
66	14/25	8/25	50 %	402,298.14	424,039.47
67	14/25	9/25	50 %	402,298.14	423,717.60
68	14/25	10/25	50 %	402,298.14	435,601.91
69	14/25	11/25	50 %	402,298.14	429,348.64
70	14/25	12/25	50 %	402,298.14	423,036.42
71	14/25	13/25	50 %	402,298.14	426,626.63
72	14/25	14/25	50 %	402,298.14	430,346.79

Table A.3: 24-bus case study mix 3: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
1	3/25	0/25	0 %	371,598.27	371,598.27
2	3/25	1/25	25 %	371,598.27	373,421.53
3	3/25	2/25	25 %	371,598.27	373,413.34
4	3/25	3/25	25 %	371,598.27	373,176.73
5	3/25	1/25	50 %	371,598.27	374,596.78
6	3/25	2/25	50 %	371,598.27	374,658.80
7	3/25	3/25	50 %	371,598.27	375,700.43
8	7/25	0/25	0 %	391,741.54	391,741.54
9	7/25	1/25	25 %	391,741.54	391,760.50
10	7/25	2/25	25 %	391,741.54	391,914.62
11	7/25	3/25	25 %	391,741.54	395,186.03
12	7/25	4/25	25 %	391,741.54	394,176.10
13	7/25	5/25	25 %	391,741.54	393,880.30
14	7/25	6/25	25 %	391,741.54	393,580.86
15	7/25	7/25	25 %	391,741.54	396,723.51
16	7/25	1/25	50 %	391,741.54	391,003.93
17	7/25	2/25	50 %	391,741.54	391,878.46
18	7/25	3/25	50 %	391,741.54	395,741.91
19	7/25	4/25	50 %	391,741.54	402,747.61
20	7/25	5/25	50 %	391,741.54	401,966.48
21	7/25	6/25	50 %	391,741.54	401,480.42
22	7/25	7/25	50 %	391,741.54	407,722.55

Table A.3: 24-bus case study mix 3: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
23	10/25	0/25	0 %	410,880.87	410,880.87
24	10/25	1/25	25 %	410,880.87	415,762.21
25	10/25	2/25	25 %	410,880.87	415,676.23
26	10/25	3/25	25 %	410,880.87	415,926.90
27	10/25	4/25	25 %	410,880.87	415,945.86
28	10/25	5/25	25 %	410,880.87	414,366.44
29	10/25	6/25	25 %	410,880.87	416,698.70
30	10/25	7/25	25 %	410,880.87	419,639.64
31	10/25	8/25	25 %	410,880.87	419,446.87
32	10/25	9/25	25 %	410,880.87	419,232.84
33	10/25	10/25	25 %	410,880.87	423,232.48
34	10/25	1/25	50 %	410,880.87	413,952.78
35	10/25	2/25	50 %	410,880.87	413,764.57
36	10/25	3/25	50 %	410,880.87	413,475.62
37	10/25	4/25	50 %	410,880.87	417,247.69
38	10/25	5/25	50 %	410,880.87	415,133.64
39	10/25	6/25	50 %	410,880.87	418,153.68
40	10/25	7/25	50 %	410,880.87	427,782.98
41	10/25	8/25	50 %	410,880.87	429,329.59
42	10/25	9/25	50 %	410,880.87	430,094.16
43	10/25	10/25	50 %	410,880.87	436,717.94
44	14/25	0/25	0 %	421,426.40	421,426.40
45	14/25	1/25	25 %	421,426.40	422,752.94
46	14/25	2/25	25 %	421,426.40	422,481.58
47	14/25	3/25	25 %	421,426.40	422,265.43
48	14/25	4/25	25 %	421,426.40	427,726.88
49	14/25	5/25	25 %	421,426.40	429,981.18
50	14/25	6/25	25 %	421,426.40	428,536.08
51	14/25	7/25	25 %	421,426.40	428,558.27
52	14/25	8/25	25 %	421,426.40	429,093.39
53	14/25	9/25	25 %	421,426.40	429,009.04
54	14/25	10/25	25 %	421,426.40	432,311.05
55	14/25	11/25	25 %	421,426.40	426,490.54
56	14/25	12/25	25 %	421,426.40	428,370.00
57	14/25	13/25	25 %	421,426.40	427,178.20
58	14/25	14/25	25 %	421,426.40	427,178.20
59	14/25	1/25	50 %	421,426.40	422,489.88
60	14/25	2/25	50 %	421,426.40	421,706.48
61	14/25	3/25	50 %	421,426.40	425,215.62
62	14/25	4/25	50 %	421,426.40	431,287.35
63	14/25	5/25	50 %	421,426.40	437,641.35

Table A.3: 24-bus case study mix 3: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
64	14/25	6/25	50 %	421,426.40	436,830.06
65	14/25	7/25	50 %	421,426.40	440,644.69
66	14/25	8/25	50 %	421,426.40	440,425.17
67	14/25	9/25	50 %	421,426.40	440,101.84
68	14/25	10/25	50 %	421,426.40	450,768.64
69	14/25	11/25	50 %	421,426.40	444,518.64
70	14/25	12/25	50 %	421,426.40	445,214.19
71	14/25	13/25	50 %	421,426.40	448,739.19
72	14/25	14/25	50 %	421,426.40	453,252.57

Table A.4: 24-bus case study mix 4: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
1	12/25	1/25	25 %	403,101.79	408,036.96
2	12/25	2/25	25 %	403,101.79	407,497.10
3	12/25	3/25	25 %	403,101.79	410,089.94
4	12/25	4/25	25 %	403,101.79	409,989.33
5	12/25	5/25	25 %	403,101.79	410,088.84
6	12/25	6/25	25 %	403,101.79	410,111.02
7	12/25	7/25	25 %	403,101.79	408,283.00
8	12/25	8/25	25 %	403,101.79	408,346.61
9	12/25	9/25	25 %	403,101.79	407,774.78
10	12/25	10/25	25 %	403,101.79	407,569.70
11	12/25	11/25	25 %	403,101.79	407,348.34
12	12/25	12/25	25 %	403,101.79	409,925.49
13	12/25	1/25	50 %	403,101.79	403,121.21
14	12/25	2/25	50 %	403,101.79	406,394.71
15	12/25	3/25	50 %	403,101.79	406,080.44
16	12/25	4/25	50 %	403,101.79	411,068.78
17	12/25	5/25	50 %	403,101.79	413,837.49
18	12/25	6/25	50 %	403,101.79	410,795.81
19	12/25	7/25	50 %	403,101.79	414,444.10
20	12/25	8/25	50 %	403,101.79	414,344.71
21	12/25	9/25	50 %	403,101.79	414,159.75
22	12/25	10/25	50 %	403,101.79	433,714.92
23	12/25	11/25	50 %	403,101.79	429,686.92
24	12/25	12/25	50 %	403,101.79	428,408.64
25	10/25	1/25	25 %	394,731.17	399,524.16
26	10/25	2/25	25 %	394,731.17	399,425.73
27	10/25	3/25	25 %	394,731.17	399,583.35
28	10/25	4/25	25 %	394,731.17	399,605.54

Table A.4: 24-bus case study mix 4: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
29	10/25	5/25	25 %	394,731.17	397,467.60
30	10/25	6/25	25 %	394,731.17	398,093.94
31	10/25	7/25	25 %	394,731.17	400,201.33
32	10/25	8/25	25 %	394,731.17	400,000.90
33	10/25	9/25	25 %	394,731.17	399,779.31
34	10/25	10/25	25 %	394,731.17	403,058.87
35	10/25	1/25	50 %	394,731.17	397,709.56
36	10/25	2/25	50 %	394,731.17	400,566.00
37	10/25	3/25	50 %	394,731.17	405,356.47
38	10/25	4/25	50 %	394,731.17	411,481.89
39	10/25	5/25	50 %	394,731.17	415,489.67
40	10/25	6/25	50 %	394,731.17	412,158.91
41	10/25	7/25	50 %	394,731.17	414,616.21
42	10/25	8/25	50 %	394,731.17	413,859.70
43	10/25	9/25	50 %	394,731.17	413,647.74
44	10/25	10/25	50 %	394,731.17	424,608.17
45	14/25	1/25	25 %	403,247.87	405,342.56
46	14/25	2/25	25 %	403,247.87	405,097.40
47	14/25	3/25	25 %	403,247.87	404,917.90
48	14/25	4/25	25 %	403,247.87	404,756.93
49	14/25	5/25	25 %	403,247.87	405,269.57
50	14/25	6/25	25 %	403,247.87	404,035.40
51	14/25	7/25	25 %	403,247.87	404,057.59
52	14/25	8/25	25 %	403,247.87	404,381.57
53	14/25	9/25	25 %	403,247.87	404,297.23
54	14/25	10/25	25 %	403,247.87	407,396.53
55	14/25	11/25	25 %	403,247.87	406,645.56
56	14/25	12/25	25 %	403,247.87	408,962.08
57	14/25	13/25	25 %	403,247.87	410,533.46
58	14/25	14/25	25 %	403,247.87	410,533.46
59	14/25	1/25	50 %	403,247.87	402,957.99
60	14/25	2/25	50 %	403,247.87	406,172.34
61	14/25	3/25	50 %	403,247.87	409,463.83
62	14/25	4/25	50 %	403,247.87	410,074.22
63	14/25	5/25	50 %	403,247.87	416,333.72
64	14/25	6/25	50 %	403,247.87	416,156.30
65	14/25	7/25	50 %	403,247.87	415,647.44
66	14/25	8/25	50 %	403,247.87	415,882.55
67	14/25	9/25	50 %	403,247.87	413,086.28
68	14/25	10/25	50 %	403,247.87	415,906.68
69	14/25	11/25	50 %	403,247.87	419,981.21

Table A.4: 24-bus case study mix 4: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
70	14/25	12/25	50 %	403,247.87	421,462.44
71	14/25	13/25	50 %	403,247.87	424,853.28
72	14/25	14/25	50 %	403,247.87	432,965.70

Table A.5: 24-bus case study mix 5: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
1	1/25	0/25	0 %	310,617.46	310,617.46
2	1/25	1/25	25 %	310,617.46	312,508.93
3	1/25	1/25	50 %	310,617.46	313,795.84
4	2/25	0/25	0 %	309,837.14	309,837.14
5	2/25	1/25	25 %	309,837.14	311,011.49
6	2/25	2/25	25 %	309,837.14	311,742.46
7	2/25	1/25	50 %	309,837.14	311,122.94
8	2/25	2/25	50 %	309,837.14	314,255.52
9	3/25	0/25	0 %	302,354.27	302,354.27
10	3/25	1/25	25 %	302,354.27	302,173.12
11	3/25	2/25	25 %	302,354.27	302,172.05
12	3/25	3/25	25 %	302,354.27	305,869.80
13	3/25	1/25	50 %	302,354.27	307,185.95
14	3/25	2/25	50 %	302,354.27	309,476.61
15	3/25	3/25	50 %	302,354.27	315,636.30
16	4/25	0/25	0 %	304,989.74	304,989.74
17	4/25	1/25	25 %	304,989.74	307,417.70
18	4/25	2/25	25 %	304,989.74	308,531.32
19	4/25	3/25	25 %	304,989.74	308,320.04
20	4/25	4/25	25 %	304,989.74	309,427.64
21	4/25	1/25	50 %	304,989.74	308,780.46
22	4/25	2/25	50 %	304,989.74	309,381.08
23	4/25	3/25	50 %	304,989.74	309,680.22
24	4/25	4/25	50 %	304,989.74	313,992.46
25	5/25	0/25	0 %	304,262.65	304,262.65
26	5/25	1/25	25 %	304,262.65	308,039.19
27	5/25	2/25	25 %	304,262.65	308,868.58
28	5/25	3/25	25 %	304,262.65	308,716.92
29	5/25	4/25	25 %	304,262.65	310,000.35
30	5/25	5/25	25 %	304,262.65	312,211.59
31	5/25	1/25	50 %	304,262.65	305,442.24
32	5/25	2/25	50 %	304,262.65	312,820.98
33	5/25	3/25	50 %	304,262.65	314,991.17
34	5/25	4/25	50 %	304,262.65	315,636.52

Table A.5: 24-bus case study mix 5: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
35	5/25	5/25	50 %	304,262.65	320,006.01
36	6/25	0/25	0 %	311,474.38	311,474.38
37	6/25	1/25	25 %	311,474.38	312,215.94
38	6/25	2/25	25 %	311,474.38	312,186.87
39	6/25	3/25	25 %	311,474.38	312,019.18
40	6/25	4/25	25 %	311,474.38	313,666.65
41	6/25	5/25	25 %	311,474.38	315,363.01
42	6/25	6/25	25 %	311,474.38	313,437.41
43	6/25	1/25	50 %	311,474.38	312,904.07
44	6/25	2/25	50 %	311,474.38	317,885.86
45	6/25	3/25	50 %	311,474.38	320,207.33
46	6/25	4/25	50 %	311,474.38	328,072.59
47	6/25	5/25	50 %	311,474.38	330,932.53
48	6/25	6/25	50 %	311,474.38	327,108.27
49	7/25	0/25	0 %	315,103.21	315,103.21
50	7/25	1/25	25 %	315,103.21	315,119.51
51	7/25	2/25	25 %	315,103.21	314,898.60
52	7/25	3/25	25 %	315,103.21	316,945.76
53	7/25	4/25	25 %	315,103.21	316,868.66
54	7/25	5/25	25 %	315,103.21	316,672.94
55	7/25	6/25	25 %	315,103.21	316,453.84
56	7/25	7/25	25 %	315,103.21	320,680.11
57	7/25	1/25	50 %	315,103.21	314,495.68
58	7/25	2/25	50 %	315,103.21	314,827.02
59	7/25	3/25	50 %	315,103.21	316,382.30
60	7/25	4/25	50 %	315,103.21	327,817.04
61	7/25	5/25	50 %	315,103.21	327,919.23
62	7/25	6/25	50 %	315,103.21	327,741.22
63	7/25	7/25	50 %	315,103.21	334,257.76
64	8/25	0/25	0 %	317,139.82	317,139.82
65	8/25	1/25	25 %	317,139.82	318,508.45
66	8/25	2/25	25 %	317,139.82	318,470.81
67	8/25	3/25	25 %	317,139.82	318,264.19
68	8/25	4/25	25 %	317,139.82	317,889.91
69	8/25	5/25	25 %	317,139.82	318,593.69
70	8/25	6/25	25 %	317,139.82	317,330.45
71	8/25	7/25	25 %	317,139.82	317,346.75
72	8/25	8/25	25 %	317,139.82	317,322.62
73	8/25	1/25	50 %	317,139.82	316,986.72
74	8/25	2/25	50 %	317,139.82	316,377.49
75	8/25	3/25	50 %	317,139.82	316,431.99

Table A.5: 24-bus case study mix 5: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
76	8/25	4/25	50 %	317,139.82	317,843.91
77	8/25	5/25	50 %	317,139.82	325,245.88
78	8/25	6/25	50 %	317,139.82	325,419.10
79	8/25	7/25	50 %	317,139.82	325,173.91
80	8/25	8/25	50 %	317,139.82	329,301.25
81	9/25	0/25	0 %	321,169.12	321,169.12
82	9/25	1/25	25 %	321,169.12	322,925.02
83	9/25	2/25	25 %	321,169.12	322,885.95
84	9/25	3/25	25 %	321,169.12	322,679.33
85	9/25	4/25	25 %	321,169.12	329,967.29
86	9/25	5/25	25 %	321,169.12	332,171.54
87	9/25	6/25	25 %	321,169.12	328,601.84
88	9/25	7/25	25 %	321,169.12	328,618.13
89	9/25	8/25	25 %	321,169.12	328,595.54
90	9/25	9/25	25 %	321,169.12	328,530.41
91	9/25	1/25	50 %	321,169.12	321,025.86
92	9/25	2/25	50 %	321,169.12	320,871.76
93	9/25	3/25	50 %	321,169.12	325,671.36
94	9/25	4/25	50 %	321,169.12	321,668.56
95	9/25	5/25	50 %	321,169.12	324,658.21
96	9/25	6/25	50 %	321,169.12	339,143.72
97	9/25	7/25	50 %	321,169.12	338,536.67
98	9/25	8/25	50 %	321,169.12	338,300.78
99	9/25	9/25	50 %	321,169.12	343,726.84
100	10/25	0/25	0 %	325,646.04	325,646.04
101	10/25	1/25	25 %	325,646.04	326,889.96
102	10/25	2/25	25 %	325,646.04	326,825.54
103	10/25	3/25	25 %	325,646.04	327,053.21
104	10/25	4/25	25 %	325,646.04	327,069.51
105	10/25	5/25	25 %	325,646.04	325,617.52
106	10/25	6/25	25 %	325,646.04	326,892.45
107	10/25	7/25	25 %	325,646.04	332,147.58
108	10/25	8/25	25 %	325,646.04	331,961.00
109	10/25	9/25	25 %	325,646.04	331,927.89
110	10/25	10/25	25 %	325,646.04	336,497.03
111	10/25	1/25	50 %	325,646.04	326,776.72
112	10/25	2/25	50 %	325,646.04	326,597.01
113	10/25	3/25	50 %	325,646.04	326,599.45
114	10/25	4/25	50 %	325,646.04	329,586.24
115	10/25	5/25	50 %	325,646.04	325,213.40
116	10/25	6/25	50 %	325,646.04	333,140.92

Table A.5: 24-bus case study mix 5: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
117	10/25	7/25	50 %	325,646.04	345,675.09
118	10/25	8/25	50 %	325,646.04	345,078.10
119	10/25	9/25	50 %	325,646.04	347,166.68
120	10/25	10/25	50 %	325,646.04	355,593.03
121	11/25	0/25	0 %	326,889.35	326,889.35
122	11/25	1/25	25 %	326,889.35	327,595.69
123	11/25	2/25	25 %	326,889.35	327,501.45
124	11/25	3/25	25 %	326,889.35	327,384.04
125	11/25	4/25	25 %	326,889.35	336,236.27
126	11/25	5/25	25 %	326,889.35	338,804.13
127	11/25	6/25	25 %	326,889.35	336,248.24
128	11/25	7/25	25 %	326,889.35	336,262.65
129	11/25	8/25	25 %	326,889.35	336,356.55
130	11/25	9/25	25 %	326,889.35	336,291.19
131	11/25	10/25	25 %	326,889.35	346,126.44
132	11/25	11/25	25 %	326,889.35	339,990.44
133	11/25	1/25	50 %	326,889.35	327,237.81
134	11/25	2/25	50 %	326,889.35	326,977.94
135	11/25	3/25	50 %	326,889.35	330,859.53
136	11/25	4/25	50 %	326,889.35	341,803.54
137	11/25	5/25	50 %	326,889.35	346,513.47
138	11/25	6/25	50 %	326,889.35	340,081.39
139	11/25	7/25	50 %	326,889.35	347,334.46
140	11/25	8/25	50 %	326,889.35	347,377.17
141	11/25	9/25	50 %	326,889.35	347,247.38
142	11/25	10/25	50 %	326,889.35	359,457.64
143	11/25	11/25	50 %	326,889.35	353,092.13
144	12/25	0/25	0 %	327,024.39	327,024.39
145	12/25	1/25	25 %	327,024.39	328,382.67
146	12/25	2/25	25 %	327,024.39	328,337.57
147	12/25	3/25	25 %	327,024.39	328,130.95
148	12/25	4/25	25 %	327,024.39	331,874.55
149	12/25	5/25	25 %	327,024.39	333,990.81
150	12/25	6/25	25 %	327,024.39	331,542.75
151	12/25	7/25	25 %	327,024.39	331,559.05
152	12/25	8/25	25 %	327,024.39	331,863.48
153	12/25	9/25	25 %	327,024.39	331,799.06
154	12/25	10/25	25 %	327,024.39	338,415.43
155	12/25	11/25	25 %	327,024.39	336,037.28
156	12/25	12/25	25 %	327,024.39	339,533.44
157	12/25	1/25	50 %	327,024.39	328,060.59

Table A.5: 24-bus case study mix 5: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
158	12/25	2/25	50 %	327,024.39	329,241.89
159	12/25	3/25	50 %	327,024.39	327,512.03
160	12/25	4/25	50 %	327,024.39	328,613.38
161	12/25	5/25	50 %	327,024.39	334,414.15
162	12/25	6/25	50 %	327,024.39	332,602.52
163	12/25	7/25	50 %	327,024.39	333,845.01
164	12/25	8/25	50 %	327,024.39	333,806.12
165	12/25	9/25	50 %	327,024.39	333,498.49
166	12/25	10/25	50 %	327,024.39	352,892.84
167	12/25	11/25	50 %	327,024.39	350,052.84
168	12/25	12/25	50 %	327,024.39	349,517.44
169	13/25	0/25	0 %	330,961.65	330,961.65
170	13/25	1/25	25 %	330,961.65	333,740.90
171	13/25	2/25	25 %	330,961.65	333,695.80
172	13/25	3/25	25 %	330,961.65	333,489.18
173	13/25	4/25	25 %	330,961.65	337,849.64
174	13/25	5/25	25 %	330,961.65	342,150.49
175	13/25	6/25	25 %	330,961.65	339,249.10
176	13/25	7/25	25 %	330,961.65	339,265.39
177	13/25	8/25	25 %	330,961.65	339,566.69
178	13/25	9/25	25 %	330,961.65	339,502.27
179	13/25	10/25	25 %	330,961.65	346,584.33
180	13/25	11/25	25 %	330,961.65	344,110.47
181	13/25	12/25	25 %	330,961.65	344,967.12
182	13/25	13/25	25 %	330,961.65	344,480.45
183	13/25	1/25	50 %	330,961.65	334,392.57
184	13/25	2/25	50 %	330,961.65	334,218.31
185	13/25	3/25	50 %	330,961.65	334,009.89
186	13/25	4/25	50 %	330,961.65	335,579.09
187	13/25	5/25	50 %	330,961.65	341,989.56
188	13/25	6/25	50 %	330,961.65	339,803.20
189	13/25	7/25	50 %	330,961.65	341,838.71
190	13/25	8/25	50 %	330,961.65	341,832.84
191	13/25	9/25	50 %	330,961.65	341,505.78
192	13/25	10/25	50 %	330,961.65	366,225.83
193	13/25	11/25	50 %	330,961.65	360,213.12
194	13/25	12/25	50 %	330,961.65	358,350.63
195	13/25	13/25	50 %	330,961.65	362,800.63
196	14/25	0/25	0 %	333,088.39	333,088.39
197	14/25	1/25	25 %	333,088.39	335,583.67
198	14/25	2/25	25 %	333,088.39	335,538.56

Table A.5: 24-bus case study mix 5: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
199	14/25	3/25	25 %	333,088.39	334,859.11
200	14/25	4/25	25 %	333,088.39	337,871.40
201	14/25	5/25	25 %	333,088.39	339,745.05
202	14/25	6/25	25 %	333,088.39	338,065.44
203	14/25	7/25	25 %	333,088.39	338,081.73
204	14/25	8/25	25 %	333,088.39	338,848.70
205	14/25	9/25	25 %	333,088.39	338,784.27
206	14/25	10/25	25 %	333,088.39	344,519.66
207	14/25	11/25	25 %	333,088.39	342,257.05
208	14/25	12/25	25 %	333,088.39	343,979.74
209	14/25	13/25	25 %	333,088.39	342,793.23
210	14/25	14/25	25 %	333,088.39	342,793.23
211	14/25	1/25	50 %	333,088.39	336,256.98
212	14/25	2/25	50 %	333,088.39	337,576.22
213	14/25	3/25	50 %	333,088.39	335,033.12
214	14/25	4/25	50 %	333,088.39	335,834.08
215	14/25	5/25	50 %	333,088.39	342,709.35
216	14/25	6/25	50 %	333,088.39	340,443.18
217	14/25	7/25	50 %	333,088.39	342,990.18
218	14/25	8/25	50 %	333,088.39	342,902.19
219	14/25	9/25	50 %	333,088.39	342,643.67
220	14/25	10/25	50 %	333,088.39	362,180.67
221	14/25	11/25	50 %	333,088.39	356,348.31
222	14/25	12/25	50 %	333,088.39	356,274.21
223	14/25	13/25	50 %	333,088.39	360,724.21
224	14/25	14/25	50 %	333,088.39	366,175.46
225	15/25	0/25	0 %	331,357.98	331,357.98
226	15/25	1/25	25 %	331,357.98	332,123.95
227	15/25	2/25	25 %	331,357.98	332,040.83
228	15/25	3/25	25 %	331,357.98	331,790.27
229	15/25	4/25	25 %	331,357.98	333,811.74
230	15/25	5/25	25 %	331,357.98	335,590.97
231	15/25	6/25	25 %	331,357.98	334,302.31
232	15/25	7/25	25 %	331,357.98	334,318.60
233	15/25	8/25	25 %	331,357.98	335,026.10
234	15/25	9/25	25 %	331,357.98	334,964.84
235	15/25	10/25	25 %	331,357.98	338,636.52
236	15/25	11/25	25 %	331,357.98	338,211.94
237	15/25	12/25	25 %	331,357.98	339,442.10
238	15/25	13/25	25 %	331,357.98	338,076.67
239	15/25	14/25	25 %	331,357.98	338,076.67

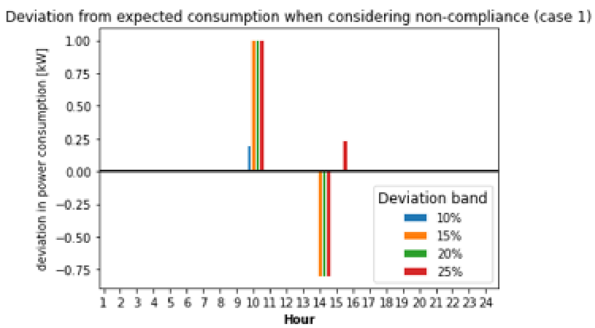
Table A.5: 24-bus case study mix 5: Operating costs.

Scenario	Manageable users	Non-compliance	Deviation band	Expected cost [$]	Real cost [$]
240	15/25	15/25	25 %	331,357.98	338,167.92
241	15/25	1/25	50 %	331,357.98	331,597.14
242	15/25	2/25	50 %	331,357.98	330,710.86
243	15/25	3/25	50 %	331,357.98	329,530.37
244	15/25	4/25	50 %	331,357.98	332,967.98
245	15/25	5/25	50 %	331,357.98	334,947.59
246	15/25	6/25	50 %	331,357.98	342,095.76
247	15/25	7/25	50 %	331,357.98	341,969.61
248	15/25	8/25	50 %	331,357.98	341,521.51
249	15/25	9/25	50 %	331,357.98	345,259.91
250	15/25	10/25	50 %	331,357.98	338,008.72
251	15/25	11/25	50 %	331,357.98	340,192.02
252	15/25	12/25	50 %	331,357.98	345,197.63
253	15/25	13/25	50 %	331,357.98	346,492.47
254	15/25	14/25	50 %	331,357.98	350,507.18
255	15/25	15/25	50 %	331,357.98	354,612.17

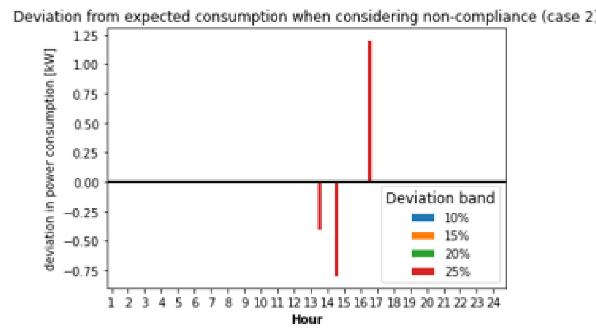
Annexes B

Deviation on randomly created users

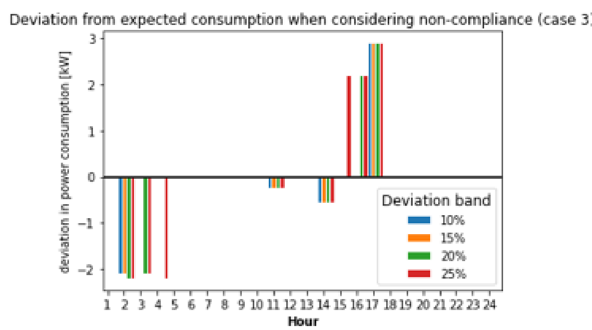
To ensure that by including deviations in ω_2 all non-compliant users modify their consumption, a sensitivity analysis is carried out to contrast how the deviation band impacts for different cases. The band selected was 25 %, as this guarantees that all users from the case study will modify their consumption. Below are graphs that show how different bands affect to the users for three cases study users by way of example. Case 2 corresponds to the user with the least sensitivity to ω_2 deviations, which made the minimum band be set at 25 %.



(a) Case 1



(b) Case 2



(c) Case 3

Figure B.1: Variations in consumption for different deviations of ω_2 values.

Annexes C

Renewable Generation and outdoor temperature

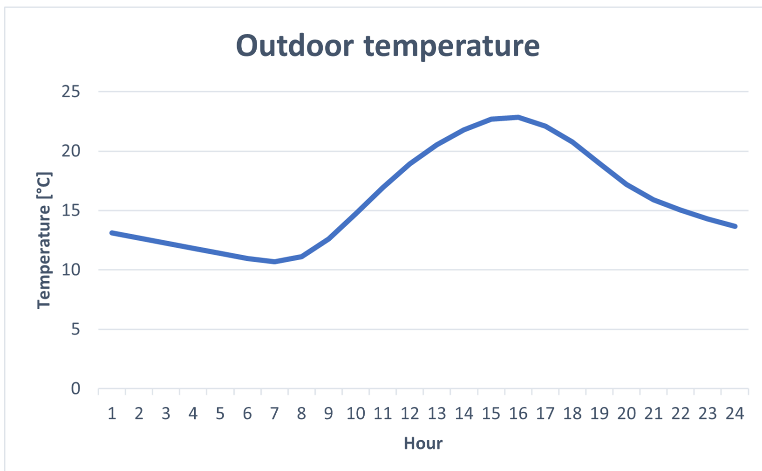


Figure C.1: Outdoor temperature used.

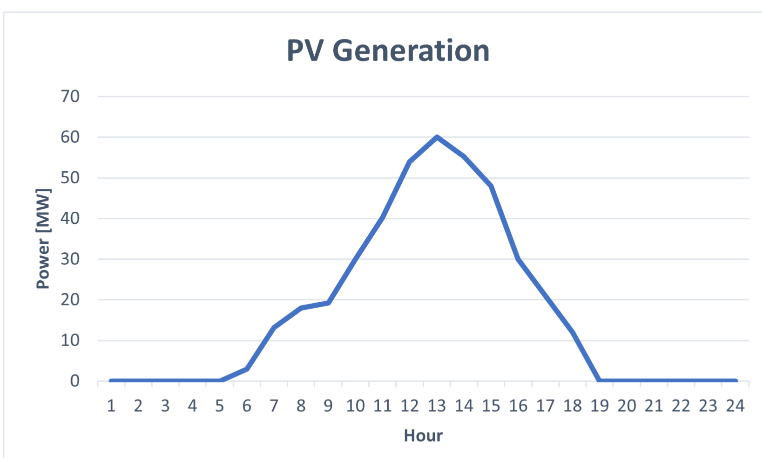


Figure C.2: PV generation used.

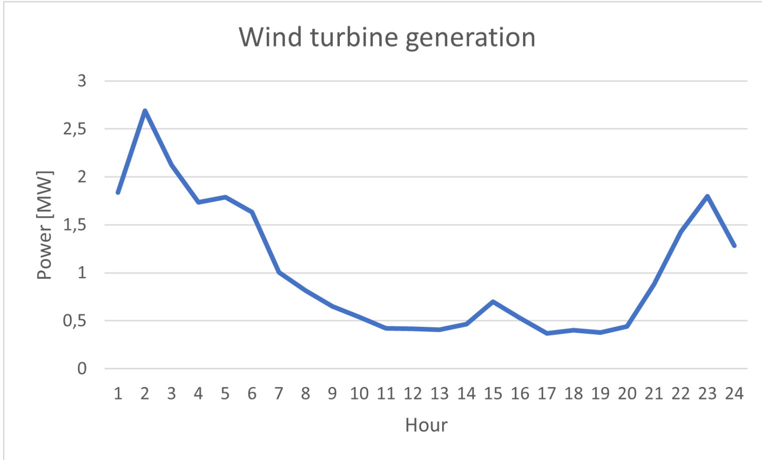


Figure C.3: Wind generation used.