UNIVERSIDADE DA BEIRA INTERIOR
Engenharia

Distribution System Reconfiguration Considering Smart-Grid Enabling Technologies

Miguel Fontes Medeiros

Dissertação para obtenção do Grau de Mestre em
Engenharia Eletrotécnica e de Computadores
(2º ciclo de estudos)

Orientador: Prof. Doutor João Paulo da Silva Catalão
Coorientador: Eng. Nikolaos G. Paterakis

Covilhã, junho de 2015

This work was supported by FEDER funds (European Union) through COMPETE and by Portuguese funds through FCT, under Projects FCOMP-01-0124-FEDER-020282 (Ref. PTDC/EEA-EEL/118519/2010) and PEst-OE/EEI/LA0021/2013. Also, the research leading to these results has received funding from the EU 7th Framework Programme FP7/2007-2013 under grant agreement no. 309048.

Acknowledgements

I would like to express my gratitude to my supervisor Professor Doctor João Paulo da Silva Catalão for his motivation and support. I am grateful for his supervision and for the opportunity that he provided me in order to give my contribution in this field under the Sustainable Energy Systems Laboratory (SES), in University of Beira Interior.

I would like to express my deepest gratitude to Engineer Nikolaos G. Paterakis for his patience and support. I appreciate how he challenged me during the course of this work, in overcoming the obstacles that were encountered in many fronts. I considered that his inputs were significant for the improvement of this work.

Finally, I would like to thank my closest friends and my family for their support, especially in difficult times. I could not have reached this stage if it was not for my parents, and for that I'm grateful.

Resumo

As constantes pressões ambientais têm vindo a pressionar a adoção de medidas eficientes no que diz respeito à conversão de energia e também à eficiência do sistema de energia eléctrica. É necessária a utilização de técnicas de optimização que proporcionem a melhoria do actual sistema eléctrico. Os sistemas de distribuição de energia eléctrica são responsáveis por entregar a energia aos consumidores finais. Estes sistemas são uma parte do sistema eléctrico que requer optimização uma vez que são responsáveis por uma quantidade considerável de perdas de energia eléctrica.

Com novos recursos disponíveis aos consumidores residenciais, como por exemplo veículos eléctricos, sistemas de armazenamento de energia e pequenas unidades de produção, podem ser vistos como uma oportunidade, e até mesmo um desafio, para os sistemas de distribuição de energia elétrica. As casas inteligentes estarão habilitadas a resolver problemas de optimização com intuito de garantir o mínimo custo da factura eléctrica, com os preços dinâmicos de electricidade. Contudo, esta optimização, por parte das casas inteligentes, pode criar problemas para os sistemas de distribuição, nomeadamente na criação de picos de carga indesejáveis durante períodos onde o preço da electricidade é o mais baixo.

A reconfiguração de sistemas de distribuição é um processo de alterar a topologia da rede eléctrica. Este processo pode ser usado como forma de minimizar as perdas de energia nos ramos de ligação do sistema de distribuição. O objectivo do operador dos sistemas de distribuição consiste em minimizar as perdas de potência activa no sistema, garantindo a fiabilidade e estabilidade do mesmo.

Nesta dissertação será apresentada uma nova estratégia de coordenação do pedido de carga do sistema de distribuição, que consiste em estabelecer uma relação entre as decisões tomadas pelo operador dos sistemas de distribuição e pelos utilizadores das casas inteligentes. Esta estratégia tem como finalidade providenciar ao operador do sistema de distribuição a capacidade de motivar os consumidores em responder, não apenas ao preço da energia eléctrica providenciado pelo mercado, mas também pelo preço criado pelo operador da distribuição. Com esta estratégia, pretendem-se evitar os problemas do aumento de perdas de energia elétrica, devido à optimização das casas inteligentes.

Esta nova estratégia é testada em diferentes sistemas de distribuição. Ainda, são utilizadas técnicas avançadas de computação com o intuito de tornar o problema de optimização viável em implementações práticas.

Palavras-chave

Otimização de sistemas de distribuição; Reconfiguração de sistemas de distribuição; Resposta da demanda; Sistemas de gestão de energia; Casas inteligentes; Computação em rede.

Abstract

The increasing environmental concerns are imposing the need to adopt actions regarding the efficient operation of the overall electrical system. Optimization techniques that pave the way to improve the current electrical system are required. The electric distribution systems (DS), which are responsible for delivering the energy to the final consumers, is one part of the electrical system that needs to be optimized, since it is responsible for a considerable amount of energy loss.

The new assets available to the residential users, such as electric vehicles, energy storage systems and small self-production units, present at the same time an opportunity and a challenge for the DS. The Smart-Households (SH) will solve optimization problems to guarantee their minimum electrical bill cost, with respect to the received dynamic electricity price signal from the retailer. However, this could negatively impact the DS by creating additional undesired peaks, during low price periods.

The distribution system reconfiguration (DSR) is the process of changing the network topology. This process can be used as a technique to minimize the active power losses on the branches of the DS. It is the objective of distribution system operator (DSO) to minimize the active power losses in this system, while guaranteeing the system reliability and stability.

In this dissertation, a new load demand coordination strategy is presented, that envisions the harmonization of the decisions made by the DSO and those made by the SH energy management systems. This strategy provides the DSO the capability to motivate the end-users, not only to respond to the retailer market signal but also to a price signal generated by the DSO. Therefore, this coordination strategy allows addressing this problem, preventing the increased losses resulting from the SH optimization process.

This new strategy is tested on several distribution systems. Advanced computing techniques are used in order to make it feasible for practical applications.

Keywords

Distribution System optimization; Distribution System Reconfiguration; Demand Response; Energy Management Systems; Smart-Households; Grid-Computing.

Contents

List of Figures

List of Tables

Relevant Acronyms

AC	Alternating Current
AMI	Advanced Metering Infrastructure
CPU	Central Processing Unit
DG	Distributed Generation
DR	Demand Response
DS	Distribution System
DSO	Distribution System Operator
DSR	Distribution System Reconfiguration
EV	Electric Vehicle
ESS	Energy Storage System
G2V	Grid-to-Vehicle
GAMS	General Algebraic Modeling System
HEMS	Home Energy Management System
ICT	Information and Communications Technology
LSE	Load Serving Entity
MICQP	Mixed-Integer Conic Quadratic Programming
MINLP	Mixed-Integer Non-Linear Programming
MISO	Midcontinent Independent System Operator
PEV	Plug-In Electric Vehicle
PMU	Phasor Measurement Units
pu	Per-unit
PV	Photovoltaic
RES	Renewable Energy Sources
RTP	Real-Time Pricing
SCADA	Supervisory Control and Data Acquisition
SG	Smart Grid
SH	Smart-Household
SOE	State of Energy
SOS2	Special Ordered Sets of Type 2
V2G	Vehicle-to-Grid
V2H	Vehicle-to-Home

List of Symbols

A. Sets and Indexes

i	Set of sending nodes.
j	Set of receiving nodes.
$(b)B$	(index) Set of branches.
$(n)N$	(index) Set of nodes.
$(t)T$	(index) Set of time periods.
$(h)H$	(index) Set of Smart-Households.
$(m)M^h$	(index) Set of Smart-appliances of residential consumer h.

B. Parameters

N_{Total}	Total number of Nodes.
N_{Sub}	Total number of Substations Nodes.
ΔT	Number of time intervals spaced in 1 hour.
λ_t^{buy}	Hourly-Variable Price of Energy bought [€/kWh].
μ_t^n	Generated DSO tariff at node n in period t [€/kWh].
$D_{n,t}$	Total demand of node n in period t [kW].
$g_{i,j}$	Series conductance in the π-model of branch ij [pu].
$b_{i,j}$	Series susceptance in the π-model of branch ij [pu].
$b_{i,j}^{sh}$	Shunt susceptance in the π-model of branch ij [pu].
P_i^{Load}	Real power demand at node i [pu].
Q_i^{Load}	Reactive power demand at node i [pu].
k	Constants used in the relaxation.
f_b^{max}	Maximum active power flow limit of branch b [kW].
R_b	Resistance of branch b.
e_{ij}	Binary parameter of line ij status: 0-open, 1-closed.

C. Variables

$f_{b,t}$	Active power flow on branch b in period t [kW].
$P_{h,t}^{grid}$	Power Supplied by the Distribution Grid during period t to the SH h [kW].
$P_{h,t}^{grid,prev}$	Power Supplied by the Distribution Grid during period t to the SH h before the announcement of the DSO tariffs [kW].
$P_{h,t}^{EV2H}$	Power Supplied by the EV during period t to the SH h [kW].
$P_{h,t}^{ESS2H}$	Power Supplied by the ESS during period t to the SH h [kW].
$P_{h,t}^{PV}$	Power Supplied by the Photovoltaic during period t to the SH h [kW].
$P_{h,t}^{in}$	Power Demand by the inelastic load during period t to the SH h [kW].
$P_{h,t}^{EV,ch}$	Power Demand by the EV charging process during period t to the SH h [kW].
$P_{h,t}^{ESS,ch}$	Power Demand by the ESS charging process during period t to the SH h [kW].
$P_{m,h,t}^{A}$	Power Demand by the appliance m during period t to the SH h [kW].
$y_{b,t}$	Binary variable of branch status: 0-open, 1-closed.
$W_{i,j}$	Variable associated with line ij in the quadratic model.
$T_{i,j}$	Variable associated with line ij in the quadratic model.
P_{i}^{Gen}	Real power generation at node i [pu].
Q_{i}^{Gen}	Reactive power generation at node i [pu].
$I_{b,t}$	Current on branch b during period t [pu].
$D_{n,t}$	Demand of node n during period t [kW].
$P_{n,t}^{sub}$	Active power provided by the substation at node n during t [kW].
U_i	Squared voltage at node i [pu].

Chapter 1

Introduction

> *"Men argue. Nature acts."*
>
> VOLTAIRE

The Modern Era is primarily characterized by the increased dependence on electricity that is considered a basic need in modern times. Unfortunately, the rapid world electrification by means of fossil fuels, used for electrical energy production, came with a significant cost. The excessive use of fossil fuels, without future planning and consideration of its sustainability, had detrimental effects on the environment and has contributed to what is described as Climate Change. The importance of this subject and the increased awareness has led to combined efforts and the creation of an international protocol, the *Kyoto Protocol*, with the aim of reducing the greenhouse gas emissions, in order to preserve the environment and promote the sustainability for future generations. The Kyoto Protocol agreement was active until December 2012, however its principles still live on. The *DOHA Amendment* came with the intent of extending the initial commitment that has been proposed, and achieve these objectives until 2020, by presenting itself as a continued effort in tackling the Climate Change problem.

To preserve the sustainability of the planet for the future generations, it is imperative to reduce the use of greenhouse gas emissions as well as to mitigate the dependence on fossil fuels. This has led humanity to rethink the sources by which the electrical energy is produced, by envisioning a new scheme of production through Renewable Energy Sources (RES). Additionally, one could not ignore the negative impacts on countries that majorly rely on fossil fuels. This dependence leads to compromised economies for the dependent countries, since oil is a volatile asset as regards its market price. This asset is continuously in high demand and it is highly susceptible to global conflicts that directly jeopardize its ability to be tradable, which leads to a direct change on its price.

The European Union has already started addressing these concerns. Through the Directive 2009/28/EC [1], the guidelines on the promotion of the use of energy from RES have been established, while Directive 2009/72/EC [2] provides the guidelines towards an open and liberalized electricity market. It is stated in [1] that 20% share of energy must be procured from RES and a 20% increase in energy efficiency must be met. The specific targets up to the year 2020 for each country are also determined in these directives. A progress report has already come to light, listing the current developments in each country [3]. However, the current economical crisis presents itself as a major setback in the initially proposed efficiency targets, slowing down the progress of all countries towards the initial objectives. Portugal, as a state member of the European Union, has already begun its efforts on achieving the 2020 goal, through several transpositions of the European directives. Still, based on the data of the last report [3], Portugal's share of RES in 2010 was 24.6% with its initial goal set to 31% by 2020.

There is a need increase the energy production from RES and also the electrical system efficiency to fulfill the proposed European targets. However, facing times of economical pressures can demotivate further investments necessary to accomplish these goals. Whatsoever, these times can also be seen as an opportunity to develop efficiency measures that can be easily adopted to ensure a more efficient electrical system.

1.1 Background

In order to meet the efficiency goals, a key element in the energy sector that needs to be optimized is the Distribution System (DS). The aforementioned European Directives [1] [2] stated the importance of each state member in improving the electrical grid. Currently, the distribution systems present a serious problem, since they are responsible for a considerable amount of active power losses. Figure 1.1 illustrates the electric power system transmission and distribution losses and its evolution over the past years [4].

According to [4], around 8% to 9% of the energy production worldwide is lost in the distribution and transmission systems. Additionally the historical evolution of losses in the European Union (average 6%) as well as in Portugal (average of 8%) is depicted. Regarding this impact and taking into the account the last year of reference of the available data (2011), in terms of the amount of energy lost in the distribution and transmission system, it represents approximately: Portugal 4 086 GWh; European Union 203 482 GWh and Worldwide 1 785 873 GWh.

For a country still somewhat dependent on fossil fuels such as Portugal, these losses cannot be neglected. Once can notice that, based on the same year of reference, that the total renewable energy production from Portugal was around 24 111 GWh. Considering this number and the total losses of that year, it is equivalent to say that it represents 17 % of renewable energy production from Portugal that is lost in these systems.

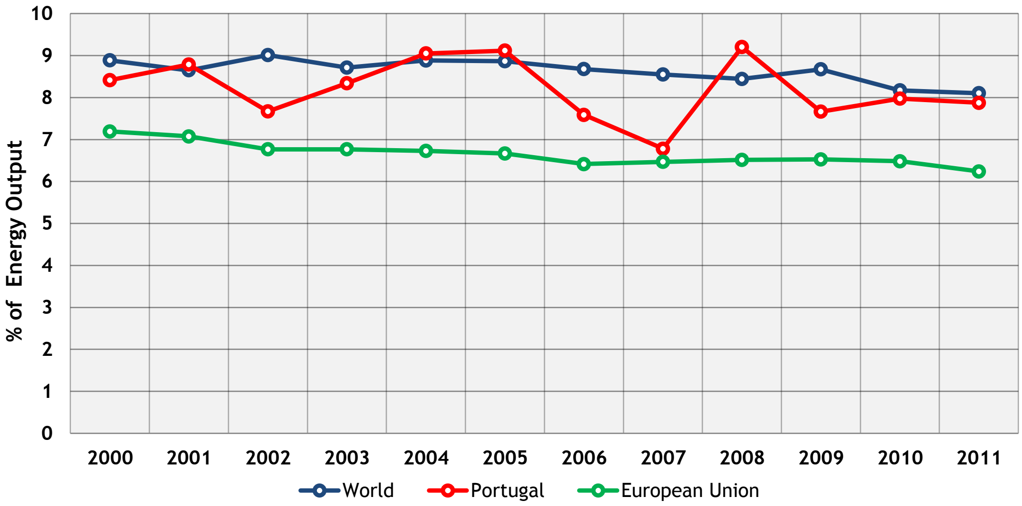


Figure 1.1: Electric Power Transmission and Distribution Losses.

Given this point and verifying the set out goals for countries like Portugal, distribution systems can present a serious setback in achieving efficiency in the electrical system.

Distribution systems are a part of the energy transport sector designed to deliver energy to the users. In many cases it is required that these systems are expanded to further address the increase in the number of users. However, it is a challenge on how to properly plan the expansion of these networks. The ineffective planning of DS and the increase of demand growth, contributes to the increase of losses.

It is expected that under the increased environmental concerns RES penetration will also increase. However, the existing electric power grid presents a serious obstacle when it comes to this matter. The existing DS works on a basic principle of energy transfer from the distribution feeders to consumers. In the past, energy production was mainly entitled to centralized power facilities. Nowadays, with the increasing introduction of RES, the production scheme is changing rapidly to a decentralized production approach. Moreover, the consumers have a great impact on speeding up this transition process. With the availability of small-scale RES behind the consumer meter, they can now become also producers in this new production scenario.

This shift of production approach presents a challenge in the current structure of the DS. An intensification of deployment of decentralized production centers attached to the DS, could increase its operating complexity, by changing the energy flow. Previously, from a centralized production scenario the energy flow worked on a single direction only, which was easy to address. However, with a decentralized production scenario, a bidirectional flow will start to happen, leading to several challenges regarding the operation and protection of the DS. Recent developments in the transportation sector with the emerge of electric vehicles (EV) are proving a reliable option towards sustainability. Nevertheless, additional challenges occur with the introduction of EVs and other dynamic loads, which the DS could not possibly support this in its current state (e.g increase in active power losses, voltage sags, line failure and even the thermal aging of power transformers [5]), unless new strategies are adopted.

To contemplate this new paradigm, the electrical power grid needs to evolve to a more robust and adaptive network, the *Smart Grid*. This new electrical grid, will rely heavily on a communication infrastructure that will help gathering information throughout the DS. With this information, a better perception of the DS operating status can be known, which aids in optimizing the network to ensure its efficiency.

1.2 Motivation and Objectives

To prevent further consequences from the climate change paradigm, and to ensure that the energy efficiency goals are met, a change must occur in the Distribution Systems. It is required an optimization in this sector, to promote the reduction of active power losses, and in the process contribute to support the increasing amount of RES production.

The need for an optimized DS while guaranteeing the system stability and reliability for the users is evident. However, in order to achieve this efficiency the distribution system operator (DSO) should no longer see the consumer as a passive element of the electric DS. The consumer actions and decisions, regarding the allocation of their load, have a direct impact on the actions that can be taken by the DSO. For the sake of the DS efficiency, the DSO needs to base its decision-making on the decisions and load profile of the consumers. The consumer actions could be worthy or a liability for the DS and its importance cannot be neglected in establishing an efficient system.

This dissertation aims to give a novel contribution in addressing the active power loss problem in the DS. It is the objective of this work to develop a decision-making tool that aids promoting a more efficient DS during its operation. Therefore, it pretends to give a significant contribution in the optimization field of the DS, by proposing a new strategy for loss reduction that could be applied in times of economical pressures and low investments in the distribution sector.

This methodology aims to create a new optimization framework, which relies on a load management coordination strategy, by establishing an interaction between the DSO and the users. This novel coordination strategy envisions the optimization of the DS by exploiting a well-known active power loss minimization technique, the Distribution System Reconfiguration (DSR). Therefore, this methodology tries to establish the interaction between the two decision makers: the DSO and the End-User. A new computational strategy is also be adopted in order to make the optimization problem suitable for practical applications.

1.3 Dissertation Structure

This dissertation is divided into 6 chapters. The current chapter, **Chapter 1**, started by introducing the research question and its problems, focusing after on the dissertation objectives regarding this research question, the optimization of the DS. The following chapters are structured as follows:

In **Chapter 2** the problems faced by the distribution systems as well as the opportunities are explained. In this chapter the techniques that can be adopted in order to minimize the active power losses are explored. Moreover, it presents typical optimization problems that are addressed in the DS. At the end of this chapter the *Smart Grid* concept is introduced, focusing on the benefits it could have on current distribution systems.

In **Chapter 3** a concept of load management that is possible by the Smart Grid infrastructure is presented. It presents the concept on Demand Response, highlighting its benefits and challenges for the DS. At the end of this chapter the latest state-of-the-art on the subject is presented, addressing the existing research gap in the field.

In **Chapter 4** the proposed model as well as its mathematical formulation are presented. This chapter starts by explaining the end-user to DSO interaction framework, explaining the fundamental concepts of this interaction. A brief explanation of the adopted computational strategy is presented, presenting its benefits in the optimization process.

In **Chapter 5** the obtained results from the proposed model are presented, presenting its behavior on different simulation scenarios.

In **Chapter 6** the final conclusions and contributions that came from this work are presented, presenting the future work possibilities.

1.4 Summary

This chapter provided a brief introduction in the research work. It started by addressing the research question presenting afterwards the motivation that leads to this dissertation with the proposed objectives. The following chapter will start by explaining the challenges and opportunities faced by the DS.

Chapter 2

Evolving Distribution Systems

> *"Everything should be made as simple as possible, but not simpler."*
>
> ALBERT EINSTEIN

2.1 Introduction

The previous chapter introduced the problematic efficiency problem that humanity faces and where it stands regarding the electrical DS. Therefore, this chapter starts by addressing the electrical distribution systems and its loss saving techniques, in order to improve its efficiency. It is explained the principles and the complexity of the optimization problems in DS, focusing on the optimization through reconfiguration method.

Later on this chapter the need for a smarter electrical grid is presented, introducing the Smart Grid concept. It starts by presenting the main contributions to the electrical system and how it will improve it, in order to meet the efficiency goals. Furthermore, it establishes the ground for the following chapter on the energy management strategy, namely demand response.

2.2 Distribution Systems

Electrical energy is a complex energy form that must suffer several transformations until reaching the final user. However, this complexity behind this structured system is not always perceived from the consumers.

Typically, the electrical energy system is organized as follows: *Production, Transmission, Distribution and Consumption.* This typical structure of power systems is considered to be based on a vertical hierarchy system, being at the top the production utilities and at the bottom the end-users or consumers, in which this principle relied on the centralized production. However, this vertical structure approach has begun to change mainly due to the introduction of RES, since it is no longer expected that the energy is produced at a centralized point but rather in many decentralized points.

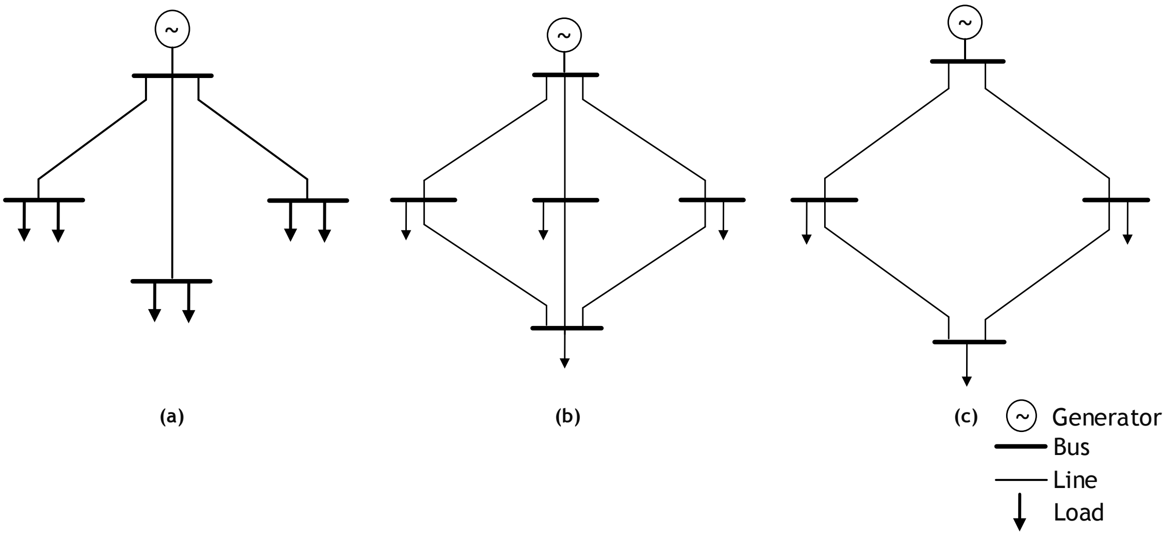


Figure 2.1: Network Topologies: a) Radial; b) Meshed ; c) Ring.

Electrical energy has a particular property in comparison with other commodities or goods: the production must always match the total consumption of the users and the losses of the system. Moreover, quality indexes in terms of frequency and voltage need to be maintained and respected in order to guarantee the stability of the system to prevent its collapse.

One of the main contributors to the energy losses, comes from the delivery mechanisms, such as Transmission and Distribution systems, that ensure the energy transport from production to consumption sites.

At the exit of a power plant, the voltage is stepped-up and is injected into the transmission system. This voltage increase is necessary to reduce the currents through the conductors while maintaining the same amount of power transmitted. Transmission systems are designed to carry energy to long distances especially in High Voltage (HV) and Ultra-High Voltage (UHV), to the receiving substations. Through this approach the use of larger diameter conductors is avoided together with investment burden and technical complexity that comes with it. These transmission lines can also be used as interconnection links. These links are mainly designed for the interconnection of different countries in order to enhance the security and the stability of the individual power system of each interconnected country, since it acts as a backup transport system in case of major outages or even in situations of high demands.

In the substations, the voltage is stepped down for the distribution network, which is the part of the network responsible for delivering energy for industrial, commercial and residential consumers in High, Medium and Low voltage. Since DS are responsible to deliver electrical energy to the final consumers, one of the main properties that it must address is the ability to be redundant, in order to prevent failure of service to the end-users. Several topologies can be adopted to ensure the operation of the energy delivery sector. In Figure 2.1 the typical topologies used in distribution systems are presented: radial, meshed and ring [6].

In the DS, the topology of choice in practical applications is radial. Radial topology offers a more straight approach in providing electricity since it allows an one-way power flow from production to the consumption side in a vertical manner.

This is particularly helpful, since it is expected the flow from one direction only, becoming easier for protection mechanisms and fault control [7].

2.2.1 Distribution System Losses

Being the element in which commercial and residential users are connected, the DS needs to be carefully planned in order to contemplate further expansion and system growth. These systems must be carefully planned in order to maintain service to the consumers in case of failure. For a successful planning the load magnitude that is being delivered must be known/predicted in order to properly dimension this network. The proper planning of DS expansion is important since it could reduce the costs of unnecessary equipment deployment. On the other hand, insufficient planning of this network could lead to weaker links in the network, which could compromise its stability. A weakly reinforced structure could lead to an overload on some branches, which could result in significant voltage drops and increased power losses [8].

In the electrical power systems an important element that has a significant contribution to the power losses is the DS. The sources of losses can be categorized as *technical* and *nontechnical* losses. Regarding nontechnical losses, this type of loss does not refer to undelivered energy for the user but rather the energy that is not being billed but is being produced. This includes losses due to metering fraud or energy theft, or even mismatch of unmetered supply and the reported billing [9].

However, its in technical losses that the attention is needed. Typically, the DS operates on low voltage levels that lead to increased currents. One can deduce from the relation $P_{Loss} = R.I^2$ that with increase of current I leads to an increase in losses, considering that R is constant. Technically the value of R can be affected by several conditions, such as temperature and frequency.

Thus, the distribution system needs to be optimized in order to increase its efficiency by reducing the active power system losses. According to [10] there are three methods that can contribute to the reduction of active power losses in the distribution systems being:

1. Capacitor Placement.
2. Distributed Generation Allocation.
3. Network Reconfiguration.

According to the first strategy, Capacitor Placement, stands for the reactive power support in order to correct the power factor and improve the voltage profile [11]. This approach tries to locally support reactive power in order to reduce the transport of reactive power, and therefore the current in distribution branches. Moreover, it prevents the voltage drops at the node, improving with it the voltage profile. However, these techniques present a challenge in the sizing and the allocation of the capacitors in the DS. It was stated before the difficulty on planning the network expansion.

Regarding capacitor placement, challenges rise on how many capacitors are necessary to ensure the desired effect. Also, if the network grows to respond to its load growth, the capacitor architecture needs to be re-sized in order to address the new expansion.

The Distributed Generator (DG) allocation method tries to introduce decentralized production points throughout the DS. Besides the contributions that are equivalent to the capacitor placement, this approach tries to locally support the power demand by reducing great amounts of energy transport in distribution branches. In the process it aids on the reduction of investing in an upgraded distribution infrastructure to contemplate the increase load. Besides the environmental benefits it has when compared to centralized production points, the deployment of DGs can locally support the voltage levels maintaining its stability. However, this approach still faces the same problem that affects the capacitor placement, its planning and allocation [12]. Poor allocation of these production centers could affect the distribution performance, since it would create an additional power flow direction that was not present in the vertical power system structure. These DG sites could even present problems in the equipment protection.

These protections, especially in the interconnection to the DS, need to be standardized in order to support different sources of DG production. This is important since, in case of faults, these DG sites if proper protection equipments are designed, can introduce fault currents in the main DS. These protection equipments are required to detect faults and prevent further damages to the system and even the DG sites. Faults with the introduction of these DG systems can create overvoltages in the system and even lead to loss of synchronization with the grid or a creation of islanded systems. These islanded systems could be a problem especially if the total DG cannot match the demand. This rises the challenge on how to properly select the interconnection transformer which is responsible to connect the DG site to the main grid [13].

Distribution system reconfiguration consists of altering network topology by opening or closing switches. Typically, DSR was used to restore system faults by putting online disabled links and for maintenance planing for security purposes. However, this method is starting to be widely used for load balancing purposes, by transferring the load from heavily loaded to less loaded feeders. By changing the network topology it can relieve the overloaded feeders and improve voltage stability and in the process reduce the network active power losses.

Of the methods presented above on saving active power losses in the DS, the DSR seems to be the method that presents a better economical option for the DSO [10]. The little investment policy on this strategy, could present itself as an attractive option for the DSO when compared to the investments required by the other strategies. However, in the practical side there are still some doubts about the cost-benefit analysis that it can bring to the DSO.

In defining a network configuration a combination of normally open switches (tie switches) and normally closed switches (sectionalizing switches) is used. These electromechanical switches, have a limited switching cycle, which affects the decision regarding the topology to adopt when it comes to cost savings. Additionally, the continuous use of these switches can result in rapid aging.

Moreover, costs associated with the field crew can also present a challenge. This could be a setback since not every switch throughout the DS is remotely controlled. This increases the crew movement to distant places that can further increase the costs for the DSO.

Additionally, the possibility of eventual short-term interruptions due to a reconfiguration process, can bring undesired failure of services to consumers incurring penalties for the DSO. Evidently, the DS without proper automation capabilities could prevent daily reconfigurations due to costs incurred. However, practically the DSR can still be adopted on seasonal periods. For instance, the DSO can have a different topology configuration for winter and summer seasons, depending on the typical load shapes of these seasonal periods, in order to minimize the operational costs.

2.2.2 Optimization Methods

In the pursuit of a more efficient electrical system, the application of optimization techniques is required. Through mathematical programming models, optimization takes its place as a mechanism of improvement of the DS, while respecting its primary principles in providing energy to the users in a more efficient way. However, optimization is customizable to the desired criteria and the objectives set by the decision maker.

Distribution system gets its attention when regarding optimization procedures, from expansion planing [14] concerns till maintenance scheduling. A good planning of the DS is essential to prevent further losses. However, while planning DS a decision maker faces critical challenges regarding the increase of consumer numbers, in other words the load growth of the system. The expansion planing encompasses the supply of energy to additional consumers without adding increased losses to the system, also ensuring the least cost possible. Moreover, the optimization problem complicates itself with the increase of DG sources.

Despite the fact that a good planing of DS is crucial, it is its operation and loss reduction that gets more attention by researchers, especially regarding to DSR. The benefits of DS reconfiguration were stated before as well as why it is the desired method in power loss savings. However, the DSR, in terms of optimization presents itself as a challenge. It should be noted that, loss reduction is not the only optimization objective in distribution networks. Load balancing is also considered in the optimization problem based on the benefits it presents. Reconfiguring the network in order to transfer the loads from heavily loaded to less or partially loaded transformers, will contribute to the improvement of voltage profile at little cost [15]. Moreover, the avoidance of long distance distribution links contributes to the system stability, since the system will have lower voltage drops [16]. The distribution network reconfiguration also takes into account system restoration, on contingencies, being as a backup system to avoid lack of energy provide to the end-user.

The most typical objective function regarding DSR is the minimization of active power losses. Typically, these optimization problems are classified as Single-Objective with the intent to find the optimal solution that provides the least losses. However, the DSR can also attend other technical or economic considerations that can be included in the objective function. In this case, the optimization problem is of Multi-Objective nature, which tries to address two or more objectives. The DSR optimization problem is subject to several constraints mainly with respect to technical limitations. These constraints aid on restricting the feasible region, preventing parameter violation and unpractical solutions. Moreover, it could lead to an increase of computational efficiency.

Distribution system reconfiguration requires the change of topology based on the switching operations. However, the question remains regarding which is the best topology for operation with respect to current network conditions. The switch component can stand two status decisions *on/off*. By the number of switching in the distribution network, with only two possible states, the network possible topologies increase as the number of switches available in the network increase. Attending graph theory concepts, in a fully connected network the total number of possible topologies that a network could have ψ is described by equation (2.1). In which B is the total number of branches in the DS and N is the number of nodes existent in the DS.

$$\psi = \frac{B!}{N! \cdot (B - N)!} \tag{2.1}$$

However, practical DS cannot be considered fully connected graphs and the expression (2.1) cannot be directly applied. Typically, these networks are weakly meshed having few connections between nodes. Thus, in order to determine the practical radial configurations of typical DS, the Kirchhoff's matrix theorem must be used. For example, considering a fully connected graph with 14 nodes, the possible number topologies are $1,07 \cdot 10^{16}$. However, the use of Kirchhoff's matrix theorem reduces the number of possible topologies to a total of 190 [17].

Still, the possible number of trees renders the DSR problem complex, representing a computational burden in terms of optimization. Considering the number of possible topologies, this optimization problem can have both continuous and discrete variables and can not be solved using classical optimization methods such as linear programming. These discrete variables introduced with the switching state, increase the complexity of the problem turning into a non-linear combinatorial problem [15]. According to the latest survey on the subject [16], the optimization methods applied to the distribution network reconfiguration can be classified as:

1. Heuristic.
    (a) Knowledge-based Heuristic Methods
    (b) Meta-Heuristic Methods & Computation Intelligence
2. Conventional Programing.
3. Dynamic Programing.

Meta-Heuristic methods solve the problem by an iteration process and are very efficient in problems of combinatorial nature. This kind of optimization needs to be adapted to the problem being optimized, giving near optimal solutions. However, this method requires that the decision-maker specifies the set of initial conditions before starting the search process based on determined criteria. In each iteration a solution or a set of solutions is found, although there is no way of the decision-maker to know if the solution or set of solutions given are optimal. Therefore, this process requires a continued iteration process until a convergence pattern is established. However, a problem presents itself on how to terminate the iteration process, by knowing if it reached convergence, since it is related to the searching parameters specified [18].

Being algorithms of iterative search nature, it opened the inspiration of searching patterns algorithms from nature. Ant Colony (AC), Particle Swarm Optimization (PSO) and even Immune Algorithms (IA) have been used to solve the reconfiguration problem based on natural pattern behavior from the physical world.

The reconfiguration problem can be seen as a Mixed-Integer Non-Linear Programming (MINLP) problem. Being a problem of non-linear nature, with new addition of possible decision (binary) variables, increases even more the problem complexity. Regarding large scale implementations, these types of problems are hard to solve becoming not suitable for practical applications. Therefore, the research efforts focus on developing linearization techniques that can provide decent approximations, which could transform the problem into a Mixed-Integer Linear Programming (MILP) problem or even a Mixed-Integer Quadratic Programming (MIQP) problem, in order to reduce the computational burden.

However, the simplifications on linearization process could lead to approximation errors that not correctly represent the original problem. Additionally, the release of some nonlinear constraints could prevent in some cases reaching the best global optimal solution of the optimization problem.

In a dynamic programming approach, the main optimization problem is divided into sub-problems. With this approach the problem is decomposed so it can increase the computational efficiency by solving each problem separately, being suitable for large-scale implementations. Despite its efficiency, some problems can not be decomposed due to its nature in order to fully exploit this capability.

It was stated before the importance of additional constraints in order to prevent unpractical topologies. Since the majority of distribution systems operate on a radial topology, the optimization problems in terms of network reconfiguration include radiality constraints that prevent infeasible topologies while maintaining the radiality. On [19] the importance and how to impose these radiality constraints in the mathematical programing models is presented.

From the DSO perspective it is important to know the response to a determined situation in order to take the best approach when regarding a particular scenario. The addition of power flow studies to the reconfiguration allow the operator to know the behavior in particular load conditions. Since the total load at each node is known and must be provided, knowing on how it is proceeded the power flow present itself as a useful tool since it can help prevent line overloading and especially transformer overloading, by providing information on the voltage magnitude. Moreover, it aids designing the topologies for typical load patterns and combine it with reconfiguration in order to save losses. Nonetheless, the addition of power flow to mathematical models increase its complexity due to its non-linearity. Moreover the increase in the number of variables from quantities to be determined contribute to complexity increase.

These optimization models need to be developed on thinking is industry applications. In terms of industry one of the main setbacks that ignore these optimization models is the computational time. As the system complexity increases, increases with it the variables and the amount of constraints to ensure the system stability at any point. After building the model the question remains: *is this model solved in an acceptable time frame ?*

Computational time could be a burden in optimization and can even demotivate the use in its application. The continued search for new strategies in the linearization process in order to increase computational efficiency, without compromising solution quality, is a wide research topic. However, this does not neglect the importance and the need of better computational strategies in order to take full advantage of accurate decision-making optimization models.

Additionally, one of the main requirements to develop accurate models that best describe the process that wants to optimize is the data availability. The quality and the amount of data available for the decision-maker plays a key role in developing models that best suits the application. In terms of distribution system reconfiguration, data on each point throughout the network helps in designing models with better constraints and operational parameters. Hence, a better information infrastructure is needed in order to optimize the DS.

2.3 Smart Grid Vision and Energy Management

With the need for a more efficient DS, a new concept rises that will aid in this endeavor, the *Smart Grid* (SG). Smart Grid is a concept that envisions the transition of the existing electrical grid to a more efficient and optimized one, relying on the bidirectional flow of energy and communication. This new grid will be efficient and secure and will base itself on intelligent computer methods to ensure its sustainability [20]. Through the communication infrastructure, it will rely on automation systems in order to grid adapt in a dynamic and intelligent way by taking the best decision on current network status.

It is expected that the current paradigm of vertical structured electrical system will be transformed. Today's electrical systems have centralized production centers, typically distanced from the populated centers, in which afterwards the energy is delivered for the industrial and residential consumers through the transmission and distribution systems.

It is envisioned through the SG concept, the shifting of a centralized production to a Decentralized Production approach. It is expected that these distributed generation centers will focus heavily from RES. These RES, such as wind and solar energy, constitute variable production sources that need to be mitigated, in order to prevent system instability on which the generation could not match the current demand. To address this concern, SG will explore the combination of RES with the use of energy storage systems (ESS) in order to compensate the lack of production. It is expected with this combination the smoothing of output production of RES, reducing the risks of power system instability.

The SG promotes the increased penetration of RES that is not currently possible in the existing electrical grid system, due to technical limitations. Exploiting DG capabilities as well as a coordination of other ES capabilities, can offer a higher opportunity of energy injection with little waste of production. Due to the resource nature (e.g Wind and Solar) there is a need for an accurate forecasting, in order to predict the variable resource, which leads to the mitigation of potential consequences. A good prediction of the production of these variable RES aids in coordinating these productions sites by expecting their possible grid injection at the expected demand.

A large number of DG centers near populating areas could significantly reduce transportation losses and also contribute to the stability of the power system if deployed correctly. Still, there are research questions that need to be addressed. For instance, how these DG sites should be seated to effectively ensure the stability of the electrical systems. Moreover, it needs to be addressed on whether or not in some cases the deployment is cost-effective when compared to centralized production sites. It is evident that DG can reduce distribution system losses in the DS, but the challenges can not be neglected especially in protection equipments since the grid will work on a bidirectional flow of energy.

There is no standard definition on how the smart grid model should be structured and there is a field of standards and regulations that needs to be developed on this sector. It is not expected that SG will replace the traditional grid due to the large logistic and investment complexity, but rather improve the existent infrastructure.

One of the main advantages of SG infrastructure is the self-healing capabilities. Through communication infrastructure and the increase of additional automation equipment, typical manual service restoration will be replaced. The electrical network can intelligently reconfigurate itself in case of link failure in order to prevent user failure of service and avoid additional system failures. The grid can effectively take decisions that best suits the current supply of energy and even assuring the optimal operation with minimal system losses.

It is expected that SG vision will enable the use of Microgrid, which consist on small islanded systems inside a Macrogrid system. Through this architecture a reliable system is created, since in case of failures the small microgrids do not compromise the entire system but rather compromises the small cell. Moreover the use of these Microgrids can prevent the losses that come with long distance transport of energy and promote the local generation of energy.

With the goals of global emission reduction of greenhouse gases, the future growth of electric vehicles industry is expected. These vehicles on the actual grid architecture would have significant impacts on its stability and loss increase, due to overloading on distribution feeders. Infrastructure reinforcement would be needed if these vehicles were to charge in current grid paradigm. However, with the introduction of SG concept two abilities could be brought. The Grid-to-Vehicle (G2V) and Vehicle-to-Grid (V2G). The principle behind G2V is the normal charging of vehicles, that the distribution grid will need to support in a secure manner without compromising the system stability. A small amount of these vehicles could be easily supported by the distribution system. However, a concern rises as regards the escalation of these vehicles that could greatly increase the system losses, by overloading the distribution feeders from the aggregated charging. On the other hand, these vehicles can also help in stabilizing the grid if coordinated properly, since they constitute a load that can absorve the production from variable DG sites such as RES in order to prevent energy waste.

The V2G approach envisions the discharge of parked EVs to the grid when the energy is most needed. The V2G can work as a backup DG system that supplies energy in high demand periods at the cost of discharging the vehicle. It is expected that, based on the consumers daily driving patterns, that the EV battery will have different states of energy (SOE). It is this state that constraints the amount of energy that the EV can supply back to the grid, since a deep discharge of the EV could compromise the battery life cycles. Still this type of EV to grid interaction could aid in load peak shaving and valley filling if done properly.

There are several opportunities and challenges with the introduction of these electric vehicles in the electrical grid. However, this EV-Grid interaction would not be possible in the current scheme of electric system but could be possible in a smart grid environment. There is an open field of optimization problems, regarding this subject on how to effectively coordinate based on different charging modes in order to reduce its impacts in the distribution network.

These strategies require a communication infrastructure that needs to be deployed throughout the system that will need to be reliable and fast in order to guarantee real-time monitor and support decision making. Moreover, the communication framework will require to be scalable to allow fast deployment in case of future network expansion. Nevertheless this will require the standardization of the communication equipment in order to ensure an easy deployment as well as promoting vendor competition in equipment manufacturing [21].

It is widely argued that one of the main contributions of the SG is the update of communication infrastructure. Typical electrical systems solely rely on monitoring systems like SCADA, to verify the status of some components on the distribution system. The SG will bring a complete set of monitoring and control capabilities that surpass the current grid infrastructure.

The SG will fully exploit and take advantage of ICT capabilities to ensure the optimization of the system while reducing unnecessary costs, such as operational and labor costs. Typically the movement of technical personnel can present as an expensive cost for the DSO and, depending on the locations, can be an inconvenient cost. The communication infrastructure will increase the knowledge and the behavior of the electrical system. Operation conditions of electrical equipment can be monitored to aid in maintenance procedures and prevent unnecessary faults of equipment (e.g transformers, substations and circuit breakers) [21].

New meters, the *smart meters* support the two way communication when compared to actual meters. Previous meters were practically only used for billing purposes. However, the new meters can gather information on the consumer as well as the utility side in order to optimize the overall system. These meters come under the new Advanced Metering Infrastructure (AMI) that SG brings. The consumers can profit from this interaction by rescheduling their appliances on a tariff that best suits them. Moreover, through these meters the view of load shape is known and it can be even used for power theft detection. The SG will escalate the deployment of monitoring and metering infrastructure. Measurement instruments such as Sensors and Phasor Measurement Units (PMU) will be present. Sensoring equipment will aid in preventive maintenance as well as the contribution to monitoring remotely distant equipment.

It is expected that these sensors will rely on the wireless technology [22] [23]. With the current expansion of the distribution grid and increased number of consumers, power quality indexes must be met in order to guarantee a proper working electrical grid. The PMU could aid in the behavior analysis of the distribution network, since this equipment can report at the point in question the actual magnitude and phase angle on the AC system. It is expected that these reading equipment would be located throughout the electrical system but properly synchronized for an accurate reading. However, a major setback that prevents the deployment of this infrastructure is the lack of equipment standards.

It is certain that SG will bring the benefits of computational efforts closer to the energy efficiency goals. Computer automation will play a key role based on the information it is receiving by the different metering and sensor infrastructure, to aid in protection devices. Although it is not only on the automation aspect that computer capabilities will show its promises. Through the communication infrastructure a considerable amount of data will be available. Network and equipment status as well as user consumption patterns throughout the network will be available for the DSO. Enhanced optimization techniques could be built facing this evolution. Instead of guessing certain behaviors of the network, the DSO would have access to real data of the current network, in which it contributes for the realistic implementation of optimization models. This could present itself as an advantage since the model complexity increases as the number of variables increase, in problems of this kind. By having access to the information several problem variables cease to exist on current methods and better system constraints can be developed to ensure optimal operating conditions and better quality indexes.

However, this scheme could increase the computational burden that will need to be addressed, since data modelling techniques will play a key role on improving the electrical system. Concerns rise regarding how to handle the amount of data generated from these monitoring equipments and how to store it, being arguably that cloud computing capabilities could be explored [24]. Although, as this communication infrastructure increases, the additional risks of data security and user privacy increase. Security issues need to be addressed in order to prevent data tampering as well as cyber-attacks that could compromise the electrical system.

Smart grid will effectively manage the electrical grid resources and optimize it considering several objectives. Utility costs will be reduced as well as emission control is guaranteed. By the introduction of RES, inefficient power plants will cease to operate, leaving it open to an increased number of DG. Moreover, energy efficiency is guaranteed if the demand profile is improved. It is during the peak hours of demand that more losses occur in the system as well as more emissions are released. A necessary management of the load profile is needed for efficiency improvement.

The smart meters will aid on this endeavor by enabling the interaction between the DSO and the consumers that is not present in the current grid infrastructure. The SG will transform the users into an active role in energy savings and efficiency through management techniques such as Demand Side Management. Through an AMI, typical homes will be transformed to smart-households with sophisticated automated systems such as Home Energy Management System (HEMS).

The HEMS system could bring some advantages for consumers as well as for the energy utilities. It will be able to control the appliances and optimize the users consumptions, based on the pre-determined criteria, specified by the user, while assuring an optimized energy use. Utilities and market structures will motivate users through incentives, making them susceptible to manage their load properly without compromising their comfort and, in the processes, contribute to a more efficient DS operation.

In Figure 2.2 it is depicted a working principle behind a smart-household (SH) and its electrical grid interaction. As stated before, one of the main contributions of SG is the communication infrastructure, in which it will be also present inside the smart-household. The element that will bridge the domain between the SH and the electrical grid is the smart meter. This instrument will be able to receive pricing and other type of signals from the market structures and the electrical grid. The SH will receive the pricing signal and respond according to it. Moreover, it can receive emergency signals from the DS in which the SH can take decisions to adequately respond to it, benefiting in the process. After receiving these signals, they are transmitted to the HEMS inside the SH.

The HEMS is responsible to coordinate the house behavior, addressing the received signals from the smart meter and also two other components: the information collected from each appliance inside the SH; the expected desired goal from the SH owner.

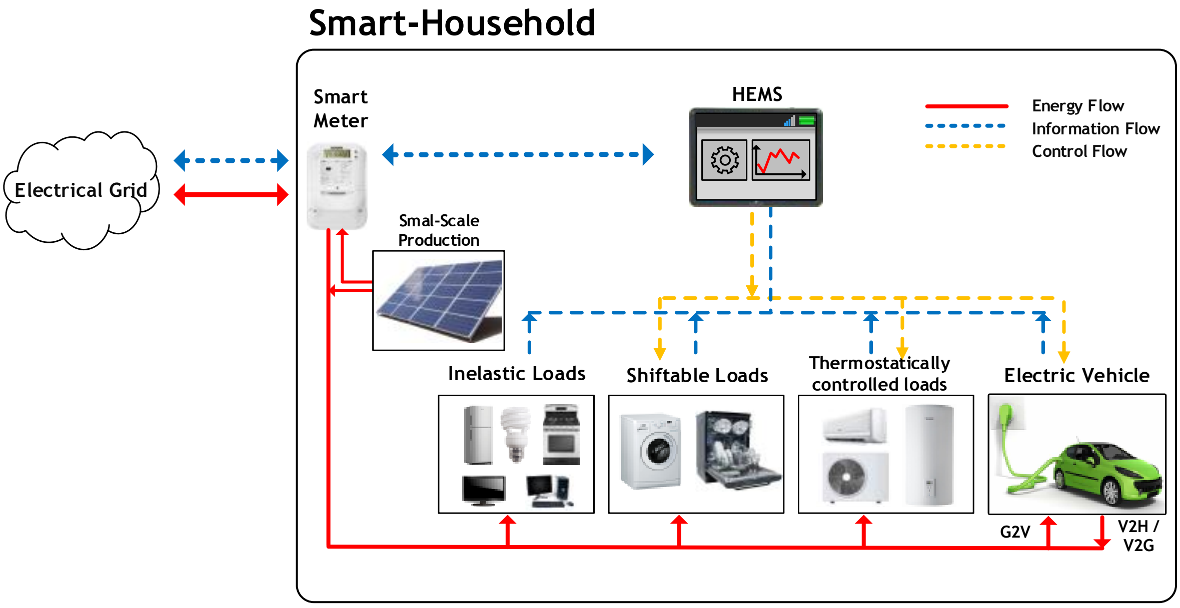


Figure 2.2: Working principle of a Smart-Household.

Typically this goal can vary between each different SH, but it is expected that the most typical goal would be the minimization of the electrical bill. Based on these three inputs, its the HEMS task to coordinate the SH, in order to accomplish the desired objective set by the user. However, not every appliance is in reach of the HEMS, and cannot be coordinated. These appliances cannot be controllable since it would directly compromise users comfort.

On the other hand, some appliances can be controlled by the HEMS while maintaining its operational constraints. These appliances are considered to be shiftable, in which a direct control does not reflect in a user compromise of comfort, and can be used to meet the desired objective. It is important to state that, it is in the control of the user to state which appliances can be controlled and it is expected that this varies from user to user.

Some loads that fall under the thermostatic category can be controlled in order to guarantee user satisfaction and minimize cost. In these cases, the HEMS system will be required to combine the monitoring capabilities (e.g monitor the temperature of a SH room). In this case, when this temperature falls under the desired set point, the HEMS sends a control signal to the designated appliance responsible for its regulation, typically the air conditioning system. The continuously monitoring will provide the HEMS the capability of taking the decision in switching (on/off) each appliance to maintain the desired set points while contributing in the process to the SH objective (e.g minimization of electrical bill).

Another controllable load that will be available for SH is the EVs. These vehicles can significantly contribute to the house efficiency. From the EVs, the HEMS receives the information regarding the current SOE. This is an important point since it quantifies the amount of energy that is available in the EV battery. Based on this amount of energy, the HEMS can take the decision while respecting the user desired time of departure.

The HEMS can decide in a direct charging procedure (G2V), with the objective of charging the battery in order to be near, or completely charged before the user departure time. However, some users will have low driving patterns in which it results in an higher SOE when they arrive home. In these cases it is possible that the HEMS take advantage of this ability in order to improve house efficiency (V2H) or even profit from grid selling (V2G). Regarding V2H, the SH can retrieve the necessary energy from the EV to be used by the appliances, avoiding the need of buying electricity in a higher price period, charging it later at a lower price. On the V2G, in case the energy is not necessary for the SH, the SH can profit from selling the energy back to the grid in exchange of benefits or a reduction in the price of the electrical bill.

It should be mentioned that to say that these two strategies will be required to respect technical constraints, such as minimum and maximum SOE of the EV. This input is necessary since it prevents a deep discharge or an overcharge of the battery, in which it could result in battery deterioration reducing its life cycle.

Hence, it is expected that the HEMS system will have significant available options regarding the optimization. Optimization problems such as minimization of electrical bill, minimization of power consumption or maximizing the social welfare are some of the examples of optimization that can be done [25]. This leads to the approach that is discussed in the next chapter, Demand Response.

2.4 Summary

In this chapter the electrical system structure was introduced, focusing on the Distribution Sector. It was presented that the distribution system is responsible for the electrical system instability, presenting afterwards how to efficiently reduce the losses that occur on the DS.

From the loss minimization techniques presented, it was stated why the reconfiguration is the method of choice by many DSOs, since it allows significant savings with little investment. Moreover, the need for optimization of the distribution system was addressed, explaining the complexity and the nature of the problem. Distribution System Reconfiguration corresponds to a Mixed-Integer Non-Linear Problem, which is computationally demanding with no global optimum guarantee, explaining the need for better linearization techniques with faster computational performance in order to create models feasible in practical time.

At the end of this chapter the Smart Grid was introduced, focusing on the improvements that will bring to the current grid infrastructure by computational and communication infrastructures. It was stated how the SG can improve the distribution efficiency and how it will effectively manage the energy resources and load patterns of the network.

Next chapter will address the Demand Response concept. Stating its objectives, benefits and challenges in adopting this management technique in face of the distribution systems, ending with the state-of-the-art survey on the subject, pointing out an existent research gap in the field.

Chapter 3

Demand Response

> *"Human behavior derives from three main sources: desire, emotion, and knowledge."*
>
> PLATO

3.1 Introduction

The previous chapter presented the issues faced by the distribution networks and also demonstrated the importance of transition of current power system structure to a Smart Grid. In this chapter, one of the main sub-domains that will contribute for the success of the smart grid is presented, namely Demand Response. Therefore, this chapter introduces the concept and its fields of application as well as its benefits and opportunities. Furthermore the challenges regarding its implementation are presented. This chapter ends with a literature survey, listing the main contributions that exist in this field.

3.2 Demand Response

It was seen before that SG has significant advantages compared to the current distribution grid structure. System stability and renewable energy integration, to lower the carbon footprint, were some of the positive arguments presented before and they constitute the foundation of the electric distribution improvement. However, one can not ignore the challenges that this endeavor presents and the complexity of the task. Typical unidirectional power flow can no longer contemplate the introduction of renewable DG sources as well as the introduction of the electrical vehicles. The end-users will need to have an active role and their participation can not be ignored in this envisioned future grid. Their decisions/actions will have direct consequences on the electrical system, since they cease to be merely passive users (consumer) to be active users (consumer and producer, the so-called "prosumer").

With the communication infrastructure from the smart grid, consumers will be aware of their consumption, prices and even the impact they have on the overall stability of the system. The responsible load serving entity (LSE), will also receive information regarding the consumers, which could present itself useful to maintain the electric power system within acceptable working parameters. However, the information alone is not sufficient to guarantee this stability without further actions.

Therefore, Demand Response (DR) tries to motivate the users to shift their typical consumption patterns into periods that best suit the distribution network. It could be defined accordingly to [26] as:

> *"Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized."*

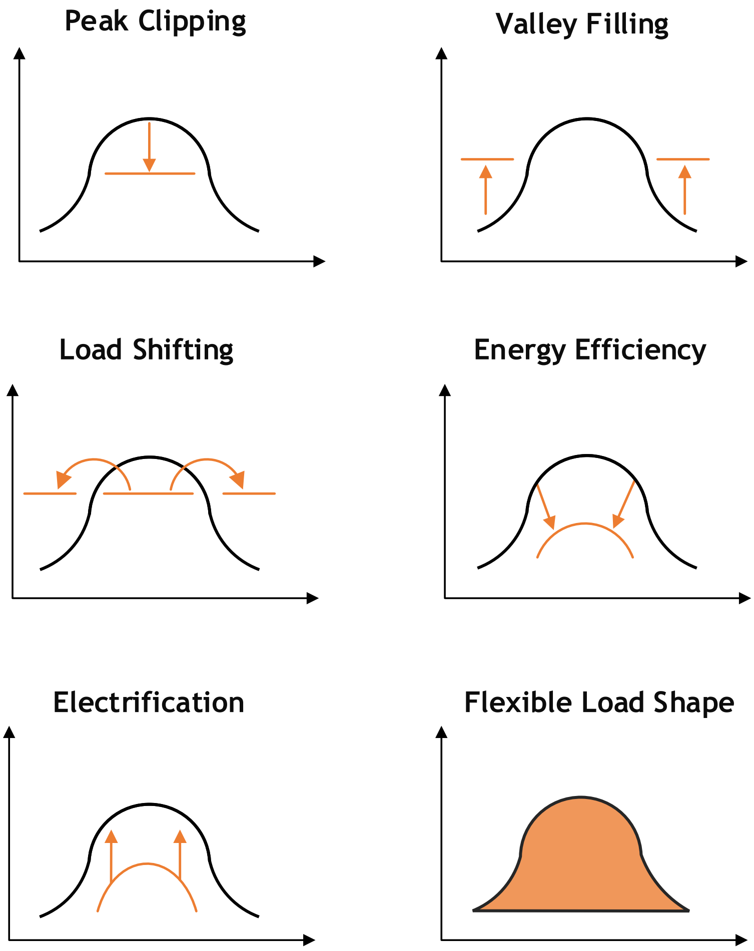
It is not the intent of Demand Response to deprive users from their energy consumption, but rather provide them incentives to, according with their needs, shape their load curve. By this approach, it is expected that it can reduce the peak load on high demand periods and start loading periods of low demand. In Figure 3.1 it is depicted the contribution that DR poses for the load shape [27]. It was stated before that one of the main contributions of DR is the reduction of peaks and also the valley filling. Reduction of peaks can come in two ways, peak clipping when the peak is removed from the system and load shifting when the load is transferred to another less loaded period, filling the load valleys in the process. The latter is the most desired approach since it does not compromise the user from their daily energy consumption but only reallocates their load smartly [28]. Another contribution of DR is the ability to have the load as an asset, to predict and in some cases control it, to give the distribution system the flexibility it needs for improving the stability of the system.

Problems in the distribution system network are a determining factor for electric system outages. The increased system losses due to the load shape is a concern when dealing with the demand. Moreover, the distribution system network planning is inefficient when regarding the costs, since they need to be planed in order to meet the network worst conditions, peak demands. Also the load valleys constitute a problem for the DS, since the distribution transformers are less efficient when they are partially loaded and it is desirable that they operate to near nominal capacity [28].

It is evident the need of reshaping the load in order to prevent further distribution problems. However, it is not expected that the consumers will opt for a manual approach, on rescheduling their consumptions, since it is not a valid option and a time-consuming task. For a successful implementation of a demand response strategy, proper infrastructure will be needed.

Advanced metering infrastructure (AMI) such as smart meters will play a key role in a DR environment. It is expected with this infrastructure that end-users will receive the price signals based on their current electricity contract, and therefore proceed accordingly in a way that best satisfies their needs. Existing meters fail to contribute to this evolution and this issue presents itself a handicap that will be addressed by the new meters.

Through current meters, users have no ability to know the behavior of the distribution network and to receive accurate price information about their load consumption patterns. With the appropriate information, consumers will have an active stance towards the distribution network and also towards their efficient use of energy. It is expected that each user will try to optimize their energy consumption based on different criteria that could be user comfort or, the most typical, the payment of the electrical bill.



Peak Clipping

Valley Filling

Load Shifting

Energy Efficiency

Electrification

Flexible Load Shape

Figure 3.1: Load shapes interaction.

It is safe to assume that with AMI, consumers will try to minimize their bill accordingly to current prices and therefore will change their consumption habits.

However, when it comes to electricity markets serious challenges arise. The fact that electricity is a resource that must be consumed at the time it is produced, makes it difficult to treat it like a normal trading resource. Current market schemes do not motivate the end-users to alter their consumption patterns. Typical electricity prices are based on flat tariffs rates, giving no or little flexibility to the end-users. Furthermore, one can not ignore the important fact that the electricity production does not always have the same production price. Typical production utilities are based on thermal cycles, and their production price greatly increases as the total load demand increases [29].

Additionally, increased loads in an unprepared system can harm the distribution system as well as the consumers. For instance, out of service distribution links due to overloading faults, can lead to increased prices for consumers due to active power losses that need to be paid. Another problem can occur with the increase of world population, for it could lead to a scarcity of production being unable to match the required demand, which could result in an increased price for consumers.

These arguments themselves reinforce the idea of a need to evolve from the existing market infrastructure to more accurate and fair demand response programs with market support. Surely, electricity markets present themselves as a set of serious challenges and is expected that combining with demand response will not be an easy task, but it will prove itself worthy.

3.3 Benefits and Opportunities

One of the main benefits of the demand response is the support of RES integration. Relatively controllable renewable productions (e.g Hydro and Geothermal) do not pose challenges in integrating in the current electric system as they can supply constant power. It is known that the main goal of producing energy from RES is the contribution to the reduction of production from the conventional power plants. However, the variable renewable energy types such as solar and wind, require strategies to fully explore the penetration of this production capacity, maximizing their power output without compromising the power system stability [30].

Due to the variability of these resources and its negative impacts on the distribution systems, some distribution system operators (DSO) opt by reducing the production capacity, to easily accommodate not so great fluctuations but in the process this results in waste of possible energy. Moreover, the unplanned reduction of wind generation can result in an overall increase of costs due to the electrical generators trying to balance the system in order to compensate the gap of production from the wind. Demand response will aid in this renewable integration by preventing its costs of integration and the waste of production [31].

A well coordinated demand response strategy will compensate this variability of production and could also contemplate the introduction of distributed generation to the distribution network, by coordinating the demand. Demand response programs will try to motivate users to shift their consumption into periods that better support the introduction of renewable energy, contributing to the environmental goals. Through this, distributed generation introduction in the distribution grid will be more efficient and will change the current paradigm of power flow. By an optimized introduction of distributed generation there will be a reduction of long distance power flow in transmission and distribution system resulting in a reduction of active power losses, especially in peak periods [28]. With this reduction in power flow, congestion in the distribution systems substations is also reduced. Voltage stability values are maintained within accepted limits by the fact that transformer overloading is prevented. Not only demand response will contribute to the reliability and security of the distribution system, but will also prevent unnecessary reinforcement investments in this sector.

Typically on electric power systems, the total installed production capacity must be greater than the system maximum demand in order to guarantee the supply for the consumers regarding different scenarios of uncertainty [30]. In extreme cases of network peaks sometimes load shedding is applied to prevent distribution system instability. However, this compromises the consumer energy use. Demand response can prevent this load shed [32] and in the process avoid system blackouts [31].

Another benefit for the distribution network is the reduction of peak-to-average ratio [33], since with coordination strategies some peaks can be reduced or even mitigated. Demand-side strategies when combined with renewable energy technologies could present an attractive option for coordination and planing. When combined with storage could present an important addition to the electric system especially to reduce the consumption on high peak periods and fill valleys on low demand periods.

A major key point in the benefits of demand response is the market contribution. Since it is expected for it to reduce the peak loads, the transmission and distribution sector will not require further major investments and costly upgrades. On the production side, it is intended to reduce the unnecessary costs coming from spinning reserve generators, which are generators that are required to increase or decrease the generation based on the current system load, leading to a removal of less efficient operating power plants [31] [32].

With proper communication infrastructure, the end-users will be aware of energy price by its corresponding time based on the accord contract. Through this information broadcast to the HEMS, it is expected to promote the overall energy savings from the end-users by motivating them to alter their consumption patterns. The end-users will have fair prices as they get informed on the status of energy production and therefore will try with this information to minimize the costs from electrical bill. It may lower costs for both utilities and consumers.

In the economic point of view, the distribution network investments are not the only reduction that comes from demand response. With stable DR systems it is expected that the market prices will decrease as much as their volatility [31]. It is important to state that the demand response will not reduce the average of energy use, rather it uses more efficiently with benefits for users and distribution system [28].

Market structures will play a key role in providing incentives to users. Several strategies have been proposed in order to incentivize the end-users to adopt a more active stance on how they manage their consumption. Then end-users will have a choice in choosing which type of tariff best suits their needs, disregarding the current flat tariffs. In Figure 3.2 the categorization of current demand response programs based on [26] and [34] is presented.

There are two main types of demand response programs, Incentive Based and Price Based programs. On incentive based programs, typically users will participate in a contract with the responsible Load Serving Entity (LSE). On the other hand, in the price based programs users will have no direct bound to the LSE, but rather respond voluntarily to the pricing signals. Some programs on the incentive based already exist regarding the classical methods. On the direct control, typically the LSE has the control over user appliances and can send them control signals to their appliances based on their consumption. Also, some LSE have the option to adopt the curtail method to provide the users monthly discounts on the load reduction they agree to give, but also it gives penalty to them if they fail to comply.

Incentives in market based structures can come in different ways. These programs are more focused on a security purpose of the distribution network. Incentives provided on emergency situations to instigate users to reduce loads on critical network situations [26]. In the demand bidding program, the users can offer their load to be curtailed at a predetermined price [30].

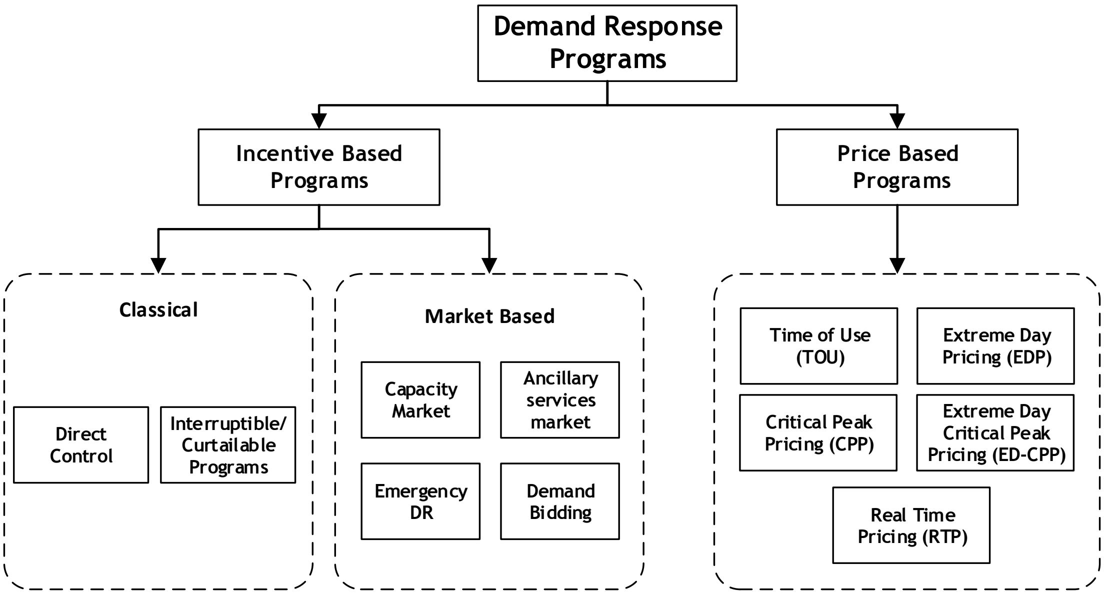


Figure 3.2: Demand response programs.

In capacity markets, users instead offer to the LSE load curtails in order to free additional capacity for the production side.

In ancillary markets, users offer themselves as standing reserves. These types of programs are also considered indirect control, since the LSE has no control over the appliances but provides the incentive to indirectly motivate the user to proceed with the action. In comparison with the direct control, indirect control is considered not to compromise the ability of the end-users to freely manage their energy consumption. However, if this approach could cause instability, the direct control could be a more preferable option [31].

Despite the benefits that these programs have for the DS, it could compromise the comfort of the users on freely using their electricity. In price-based architectures, users can benefit and exploit more their load reallocation through the price signals.

Time-of-Use tariffs (TOU) require low investments for its implementation and aims to differ the prices from low to high peak periods. On high demand peaks, the price its at its high value in order to prevent the consumer to allocate load in that period. And in low demand periods, typically at nigh periods, the prices are lower in order to motivate the users to fill the valley that occurs during nighttime. Considering that this strategy requires little investment, it has been adopted from many LSE [34]. Critical Peak Pricing (CPP) is based on events and its mainly activated on compromising stability or during contingencies. On Extreme Day Pricing (EDP) the principle is similar, however the prices do not change after the pricing period but are maintained for the whole day.

Of all the programs illustrated in Figure 3.2, RTP seems to be the most promising pricing scheme [33] [28] [34]. Despite being a complex tariff system, RTP presents itself as the most fair solution for the consumers.

Through this mechanism, consumers will be able to receive the actual production prices and also the losses from the production center till the consumer point. Additionally, consumers will exploit RTP to its advantage being even more motivated to adhere in shifting appliances when compared to flat tariffs. Furthermore, industrial consumers that present significant load demands, could be significantly motivated to change their patterns due to their high incentive benefit when compared to residential loads.

3.4 Challenges

There are several key aspects that need to be addressed if demand response is to succeed. The lack of proper communication infrastructure will be a liability if not implemented correctly [30]. One can not hope to motivate the end-users to change their daily consumption patters if they are not aware of the current electricity prices and the DS status. A bidirectional communication architecture needs to be deployed if the users are to receive relevant information and in the process provide information on their current load patterns. The development of standards and protocols presents an obstacle to an efficient communication [31]. Even though, it has not been agreed yet to use a robust communication infrastructure in order to motivate the equipment manufacturer to start producing according to that standard.

Residential consumers see themselves as small loads, when compared to industrial ones, and typically they are not motivated to manually shift their appliances in order to take advantage of market prices. This is a time consuming process and the financial gains are not so evident. Clearly, AMI could change this paradigm as the consumer decide regarding their loads without manual contact with the equipment. Smart meters will play a key role, since they receive the market signals or DSO signals with prices to inform the end-user. However, the cost of upgrading to this infrastructure is yet to be known.

It is evident that consumers concern will rise about security of their data. Consumers could be skeptical of possible security flaws that could compromise their data leading to a privacy violation [35], since the HEMS represents the entry point of all appliances control and contains the monitoring information of the building energy usage [33].

Direct control strategies will rely heavily on computational requirements when compared to indirect control [31]. Despite the already required communication infrastructures needed for information control, a simple point that a DSO could have control on consumers appliances bears to understanding the necessity for these requirements. Direct control requires the direct interaction between consumer appliances and the responsible coordinator, in this case it is assumed to be the DSO. Indirect control does not require such computational effort since it tries to achieve the same goal with incentive programs or monetary rewards. With this indirect control approach it is expected that the responsibility of the power system stability will be passed on from the DSO to the end-user. With this transfer of responsibility, a proper market framework is needed for the demand response, in order to properly motivate consumers. Small incentives could not be significant enough to motivate a consumer to adhere in his/her load schedule.

The electrical bill management is not so attractive when comparing to the typical overall house budget. In addition, it is expressed in [31] the concern that RTP could provoke the user fatigue when following this program, since it requires a constant interaction of load change to the price incentives and could lead to some user discomfort after a certain point. This could present a serious problem since the market stability could be compromised and the demand response could not be achieved.

The market framework presents at most, a more challenging point than the technical one, and a poor market framework can be a major setback for the success of demand response. With the introduction of RES in the electrical grid, an expected behavior is the overall electricity price drops. Even so, there is a need to evaluate the price drops and the impacts that DR provokes on the electricity prices. One can surely agree that the demand response also constitutes an unpredictable electrical response, since it depends on the amount and the behavior of the users that participate on the demand response programs. In the electrical distribution point of view, this cannot be left to random and from there will be a need for realistic forecasting models in order to quantify this market impact and, in the process, predict the response behavior of the consumers and their impacts in the DS. Forecasting the variability of variable energy resources is already a challenge and when it comes to consumer behavior it will present a different one since the market operator must take into account that the response of the consumers is not immediately translated to market behavior. Moreover, different users motivate themselves by different motivation factors. Hence, market operators will require to predict the fair prices based on the consumers response and their impact on the market behavior. For instance, the introduction of RTP program will require advanced forecasting techniques, especially in short periods, in order to take into account the variable generation of RES as well as expected users actions [32].

Assuming that reasonable market forecasting models are created, there is still the question on how to currently establish the pricing of DR. The question arises on how to quantify the value that demand response has on the electric power system. Marginal cost pricing can not simply be implemented since there is not a direct fuel equivalent. Considering that an increasing number of renewable penetration occurs due to the demand response programs, marginal pricing as it is relates to the thermal equivalent of power utilities, based on cost components of generators and auxiliary equipment. On thermal utilities it is typical as the price curve per power production increases, the marginal price is calculated [29] [36]. The question remains, how should demand response be priced considering capacity and generation costs, since there is no direct fuel equivalent for the demand in order of the generator and the production of variable renewable sources, which could difficult the quantification of electricity price.

Finally, a valid concern rises regarding the optimization done by the users. It is expected that in some cases a conflict of optimization strategies might occur. For instance a consumer that possesses heating/cooling appliances with a determined set-point and an optimization that is done regarding the least cost for the electricity. It is highly probable that some infeasible scenarios might happen by only taking into account the cost minimization, since this optimization could violate the predetermined set points for user comfort. Different allocation of priorities can be set in order to prevent this kind of problems, and probably will require at some point the manual input of the consumers on their desired expectations.

3.5 Literature Survey

Since the demand response systems will depend on residential participation, the load modeling is an important point of concern. The need to predict the behavior of controlled and uncontrollable loads, also known as load forecast, is very important in the perspective of the distribution system. To accurately design DR, the power consumption and load profiles of the households must be known, and several studies already started to appear in this field.

Several studies ([37],[38],[39]) present the modeling of typical cooling and heating appliances, such as water heaters and air conditioning systems. These models are developed taking into account the appliances operational specifications, and they also present the benefits of the control use of these equipments. In [40] a control strategy of thermostatic loads is proposed that keeps track of each appliance power consumption profile. This modeling of different types of loads is also considered with variable energy sources systems (e.g Wind). In [41] addresses coordinated heating appliances, in order to assist the balance of wind power generation and prevent the loss of excess power production. One basic method to predict the consumption of each appliance is by allocating a metering device to each appliance. However, this presents a practical implementation concern, with the amount of metering components required to gather the data. Since the equipment cost is a concern, in [42] a strategy is proposed to estimate individual SH appliance loads, from the aggregated signal provided by the smart meters.

These studies presented the modeling of typical load appliances. Yet, another type of load is getting its focus, the electric vehicles. Compared to the typical home appliances, the EVs are more difficult to model. These vehicles present an increased level of freedom and cannot be so simply controlled without compromising the user satisfaction. Due to the travel distances, the EV state of energy (SOE) is not always the same and could present a challenge in the coordination of the charging procedures. The new addition of EVs could present a serious challenge as well as an opportunity for the electric power systems. Considering that one of the main goals of the DS is the minimization of the distribution network losses, the charging of these vehicles could present an obstacle to this objective. Voltage deviations, transformer overloading and increased line losses are some examples of typical problems that come with the increasing number of electric vehicles. The undesired peaks could compromise the power quality for the end-users as well for a solid functioning electric grid system [43].

Therefore, the charging process cannot be uncontrolled, otherwise additional infrastructure investments would be also a problem for the distribution network operator and would not contribute to the overall system efficiency. In order to prevent these problems, a coordination system is needed. In [43] the power quality improvements that comes from a coordinated charging strategy are presented and also alerting to the impacts from the uncoordinated charging process. An optimization problem that envisions the reduction of voltage deviation and power losses from the distribution system was solved. These impacts are already getting their attention by the scientific community as well as from the industry.

It comes to light studies that propose to analyze the impacts that EV have on the contribution for DS losses [44]. The same study presents the analyzsis of the investments that come with the EV charging infrastructure, and it is stated that these investments could be higher in urban areas with high load density. Nonetheless, it reinforces the idea that a coordinated charging can contribute to reducing these investments.

Since the coordination could be the expected scenario, some opportunities may rise. Users that have a daily habit can charge their vehicles during the night. To an accurate coordination system, some information must be known for the distribution system; time of arrival, departure time, state of energy of the battery are some examples of "must know" quantities for an accurate schedule. Due the variability of the users daily pattern, it is a challenge to predict these behaviors. Already this concern is being addressed by the scientific community. In [45] the impacts of the EV charging in a urban area taking into the account information such as demographical data and driving patterns are studied. Other studies try to model the impact that the charging has on residential areas. In [46] the charging strategies of an apartment with photovoltaic systems and different charging strategies are discussed.

Since the end-user is the main factor that will dictate when and where to charge, it is expected that it will try to do it in order to minimize its charging costs. When an increasing number of consumers try to minimize their costs, the allocation of the charging procedure in a low price hour could create an undesired network peak that was not there in the first place. With this in mind, the coordination problem of EV charging cannot be solely done regarding the optimization of minimum cost for the consumers. From the distribution grid perspective, some physical limits of the electrical equipments must be respected, and this increases the complexity of the coordination. A recent study [47] presents a charging strategy taking into the account these network constraints like voltage stability, and presents the strategy like a linear optimization problem which is an important fact in computational efficiency.

In [48] two different optimization problems regarding the EV charging are presented. The two optimization problems that are presented are a network optimization, that tries to mitigate the increased loads due to charging, and other optimization objective that tries to minimize the charging costs based on the market prices. Based on the results presented, the charging of EVs based only on the electricity price could produce increased network loads and undesired peaks, leaving it an undesired situation from the network operators perspective. On the other hand, regarding the network problem optimization, that gives the charging control to the network operator, it is found that less network infrastructure reinforcement is needed. It is expected that a better demand response system takes into account the charging scenarios based on the price and also based on the distribution network constraints, seems to be the most beneficial solution.

These studies stated above present some examples of research topics in the charging strategies. Another related field rises with the introduction of electric vehicles and their contribution. The introduction of electric vehicles could introduce some benefits, known as Vehicle to Grid (V2G) and Vehicle to Home (V2H). Regarding the V2G, the discharge of these vehicles can contribute, when coordinated, to a more balanced and robust electric power system and it could be considered an asset in the distribution system perspective.

With the V2G, several technical aspects are improved such as reactive power support and additional power regulation as well as load balance and harmonics filtering. Another advantage of this concept is the added support on the integration to the intermittent power sources, such as wind and solar power. Therefore these vehicles are not only loads, but can act as a storage system or even a generation system. In [49] the storage capabilities of electric vehicles in power systems, considering battery specifications and electricity prices are studied.

It was stated before that the charging strategies of these vehicles must be carefully planned, otherwise undesirable peaks are created. If not done properly, there could be an increased cost of supporting infrastructures for the charging procedures. However, some concerns exist regarding this technology (V2G). When it comes to battery life cycle, it could be significantly reduced due to the bidirectional power flow instead of a typical unidirectional one [50]. Without this technology an unidirectional flow is present (charging process), but with the addition of the discharging to the grid an additional flow is created.

Additional monitoring infrastructure is needed in order to accurately implement this technology. Smart meters will help in controlling the charging process in order to prevent unnecessary losses derived from the charging. Besides the automotive and oil industry pressures, social and technical obstacles are still the main source of concern when regarding the successful implementation of electric vehicles in the DS. One could argue that the expected optimization done by the smart houses would be the optimization based on the least cost payment of electrical bill based on current pricing signals, without compromising their commodity and their habit patterns. Typical price rates, such as the flat rate price, do not motivate the end-user to have an active stance regarding the energy consumption. It is the intention of dynamic pricing schemes, to motivate the end-user to smartly reallocate his/her energy consumption to periods that better advantages bring to the distribution system. By this dynamic pricing scheme, the end-user, after solving the least cost optimization, can be motivated to change some load to least cost prices which typically represent low loads on the distribution side. Regarding these optimization based schemes, several studies exist.

Within the SG environment it is expected that each SH will have a HEMS. This HEMS will allow bidirectional flow of information, which allows to receive the price signals and act accordingly to what fits best their purposes and benefits. Therefore, in [51] an algorithm that will be processed by the HEMS in order to minimize the electricity bill from the pricing signal is proposed. A residential load control strategy was proposed in [52]. This strategy considered that each residential house has a smart meter with communication capabilities. Since demand response capabilities require that the users shift loads from off-peak periods, this could present an inconvenient from the end-users perspective. On this study, the users specify the required time of operation for each appliance. Therefore, the main goal of this study was to minimize the payment of electricity, based on RTP price scheme, without compromising the operation of the users appliances. Evidently, by this approach a shaping of demand curve is proposed and it is stated that it can reduce the peak-to-average ratio. Nevertheless, this is not the only study that addressed the benefits of a coordinated demand response to the peak-to-average ratio. In [53] it is explored with electricity storage and its impacts to the peak-to-average ratio reduction and in [54] a scheme to reduce the peak-to-average ratio based on real-time pricing is proposed.

A reward strategy is proposed in [55]. It aims to give the end-users a reward based on the amount of load that is shifted and based on their contribution to the distribution system improvement. Based on the information retrieved from smart meters, this study aimed to contribute to the peak shaving and also to improve the voltage stability by reducing the transformer overloading. Another incentive scheme is proposed in [56]. This approach combines incentives and RTP pricing to minimize the cost for the consumers, and also tries to minimize the overloads on the distribution feeders. These incentives come as adjustments to the electricity prices and its given the end-user the option of decision by accepting of rejecting these incentives as they are offered. Therefore, these strategies try to motivate the consumers to shift their load from overloaded to non-overloaded periods, and in the process contribute to the overall stability of the distribution network.

It is proposed in [57] a demand response strategy based on Time-of-Use (TOU) pricing that establishes a communication between the consumers and the utility company. In this approach, the daily consumption of end-users is forecasted. After the demand forecast of each individual user, the demand is aggregated and then presented to the utility company. The utility company after receiving this information, communicates back the TOU prices, leaving the end-users the ability to reschedule their loads based on this price.

A recent study [58] proposes an automated strategy for demand response. A control strategy of different appliances with respect of the price signal is proposed. Also, several power constraints are considered. Apart from the market price signal, a price penalty signal is created to prevent the creation of network consumption peaks. Studies like [59] address the demand response applied to industrial facilities. Several of these studies tried to establish the relation between end-user and the distribution system operator, in order to contribute to the overall efficiency of the electrical system and also to provide the consumers the least price that can pay. In [60] the effects of demand response in the distribution power system constraints are studied. In this model, it is considered that the users sign a contract with the load service entity that allows the control of their appliances, if needed to regulate the system so it stays below operation limits on peak hours. The LSE achieves this by sending control signals to the end-users HEMS in order to coordinate the appliances so as to meet system objectives. Also in this study a formulation of the optimal power flow (OPF) to verify the benefits of the model is presented.

However, this is not the only study that uses the OPF to study the impacts on the distribution systems, since in [61] it is proposed a coordination model that envisions the minimization of the feeder losses with distribution power flow. In this method the loads to be controlled receive control signals in order to alter the energy use patterns. In [62] a strategy that tries to reduce the distribution active power losses is proposed. In this demand response environment, it is considered that each user posses two objectives. An individual objective that tries to optimize their consumption pattern, and a common objective, that tries to optimize in the process the distribution losses without violating the capacity constraints.

Despite all the efforts done in this field there is still a research gap existent. All the studies presented aimed to minimize the cost for the consumers and some even take into the account some aspects of the distribution system stability. However, none of these studies presented the benefits of combining the demand response coordination strategies with the distribution system reconfiguration, which is a novel contribution this dissertation provides.

In the previous chapter the benefits that come from the distribution network reconfiguration as well as active power loss reduction without actual investments from the part of the DSO were stated. Only a recent study [63] tried to bring into light the idea of combining DSR with DR. However, this approach is not so desirable since it leaves to the DSO the full control of the SH loads, leaving no space for the end-users to freely schedule their electrical appliances. A strategy that combines the DSR and DR is needed, but that leaves the decision for the consumers rather then the DSO. Therefore, reconfiguration and a well designed coordinated strategy of demand response could probably lead to bigger savings in active power losses.

3.6 Summary

In this chapter one of important concepts of the smart grid was presented, namely Demand Response, and its impacts and challenges in the distribution network as well as its benefits if a successfully adopted were discussed. Then, the state-of-the-art on the subject, highlighting the contributions that have been made in several areas on the demand response.

Regarding the end-users optimization, the main focus is the minimization of consumer electrical bill that can be done by reallocating flexible loads to lower price periods without compromising the consumer comfort.

From the presented state-of-the-art, it was rendered that the end-user to distribution interaction was mainly focused on local power constraints. It showed the gap of knowledge that exists in combining coordination strategies with distribution network reconfiguration.

The following chapters present the proposed method and its mathematical formulation as well as the results and conclusions regarding the proposed methodology.

Chapter 4

Proposed Model and Mathematical Formulation

> *"Measure what is measurable, and make measurable what is not so."*
>
> GALILEO GALILEI

4.1 Introduction

At the end of the previous chapter a literature survey was presented, pointing out the existent research gap in the field of load management coordination strategies combined with DSR. In this chapter, the proposed model and its mathematical formulation are presented.

Firstly, the problem that could be created in the SH optimization and its direct impacts on the DS is demonstrated, by presenting a typical Smart-Household optimization problem and explaining its working principles. Afterwards, the mathematical formulation on the DSO optimization problem is presented. The optimal reconfiguration problem is explained and then a network analysis tool is presented.

Finally, the novel coordination strategy between the SH and the DSO is presented, explaining its interaction framework and how state-of-the-art computational techniques can be exploited in order to achieve increased computational efficiency.

4.2 Smart-Household Model and Working Principle

As stated before, it is expected that each SH equipped with HEMS will solve an optimization problem, especially regarding the minimization of its electrical bill. Thus, a typical objective function is displayed in equation (4.1), in which TC_h represents the total cost for each SH h; $P_{h,t}^{grid}$ is the energy that each SH directly consumes from the distribution grid that it is charged at the current market price signal given by λ_t^{buy}. It is considered that this price changes hourly, resulting in $\Delta T[h] = 1$. Without loss of generality, the ability of each SH to inject energy back to the grid is neglected. Considering this capability is straightforward and would result in a modification of the objective function (4.1), to include the selling prices and the amount of energy sold.

$$TC_h = \sum_t (P_{h,t}^{grid} \cdot \Delta T \cdot \lambda_t^{buy}) \tag{4.1}$$

The entire energy supply of a typical house is provided by the DS. However, it is expected that in SH this condition will no longer hold, since it will be able to receive energy from other available sources within its structure. Still the energy balance must be respected, as it is described by equation (4.2). For a given house, the total amount of energy that is supplied must match the energy demand required by that house. For typical houses, this would result in $P_{h,t}^{grid} = P_{h,t}^{D}$, being $P_{h,t}^{D}$ the total demand of the house h at a given period t.

$$\sum_t P_{Supplied} = \sum_t P_{Demand} \tag{4.2}$$

However, in a SH the energy balance may be satisfied by several alternative sources. It is expected that, a SH will contain an EV, an ESS and a PV system that can be used to satisfy the energy demand of the house. This leads to equation (4.3), which represents the power balance for a given SH h in a given time t. On the left side of the equation, the supply part, each SH can now, apart from the power provided by the grid ($P_{h,t}^{grid}$), have energy contributions from the EV2H ($P_{h,t}^{EV2H}$), ESS2H ($P_{h,t}^{ESS2H}$) capabilities and the production from the PV systems ($P_{h,t}^{PV}$). On the other hand, the right side of equation, which represents the SH demand is decomposed into several parts. Even with an HEMS system in each SH, some loads cannot be controlled, since their working behavior cannot be compromised since their interruption would bring direct load comfort to the end-user. Loads that fall under this category (e.g TV,oven, etc.) are considered inelastic loads ($P_{h,t}^{in}$). However, several types of loads can be controlled and can change their time of operation such as the EV charging ($P_{h,t}^{EV,ch}$), the ESS charging ($P_{h,t}^{ESS,ch}$) and all the smart appliances that have the ability to be controlled ($P_{m,h,t}^{A}$). The notation m stands for a given smart appliance that exists in the SH (M^h).

$$P_{h,t}^{grid} + P_{h,t}^{EV2H} + P_{h,t}^{ESS2H} + P_{h,t}^{PV} = P_{h,t}^{in} + P_{h,t}^{EV,ch} + P_{h,t}^{ESS,ch} + \sum_{m \in M^h} P_{m,h,t}^{A} \; \forall t \tag{4.3}$$

Furthermore, several operational constraints must be added in the optimization problem. Constraints such as the ESS technical specifications to prevent its min/max capacity violation and discharge and charge rates are also included. Similarly, regarding the EV, capacity constraints, charging and discharging rates, and additional constraints, like time of arrival and time of departure are used to ensure that the vehicle is decently charged before departure, according to the users driving patterns. These operational constraints can be found in [63], [64] and [65] and are not repeated here since the SH model is only used in this work to demonstrate the benefits of the proposed coordination strategy.

Regarding this, given the specific equipment ε, one can state that the x_ε represents the vector of decision variables that are feasible in the region of S^ε that is a subset of SH optimization problem feasible region S^h. Being these constraints applied for every equipment operating inside the SH, that contributes to the power balance, the constraints for PV, smart appliances, EV and ESS are expressed in equation (4.4).

$$\begin{aligned}
&x_{PV} \in S^{PV} \subset S^h \\
&x_{SA} \in S^{SA} \subset S^h \\
&x_{EV} \in S^{EV} \subset S^h \\
&x_{ESS} \in S^{ESS} \subset S^h
\end{aligned} \tag{4.4}$$

Following these equations, the objective function and the applied constraints of the optimization problem that each smart-household must solve is concisely described by (4.5). Each smart-household will solve this optimization problem aiming at the minimization of the electrical bill. This is achieved by trying to minimize the power procured from the grid in instance t with respect to the price signal in that period λ_t^{buy}. The SH will coordinate the use of appliances and the available resources in order to maintain the SH power balance, while satisfying the operational constraints of all its assets.

$$\begin{aligned}
\text{minimize} \quad & TC_h = \sum_t (P_{h,t}^{grid} \cdot \Delta T \cdot \lambda_t^{buy}) \\
\text{s.t.} \quad & x_{PV} \in S^{PV} \subset S^h \\
& x_{SA} \in S^{SA} \subset S^h \\
& x_{EV} \in S^{EV} \subset S^h \\
& x_{ESS} \in S^{ESS} \subset S^h \\
& \\
& P_{h,t}^{grid} + P_{h,t}^{EV2H} + P_{h,t}^{ESS2H} + P_{h,t}^{PV} = \\
& P_{h,t}^{in} + P_{h,t}^{EV,ch} + P_{h,t}^{ESS,ch} + \sum_{m \in M^h} P_{m,h,t}^{A} \ \forall t \\
& \\
& P_{h,t}^{grid}, P_{h,t}^{EV2H}, P_{h,t}^{ESS2H}, P_{h,t}^{PV} \geq 0 \\
& P_{h,t}^{in}, P_{h,t}^{EV,ch}, P_{h,t}^{ESS,ch}, P_{m,h,t}^{A} \geq 0
\end{aligned} \tag{4.5}$$

In order to demonstrate the behavior of the SH optimization, a brief explanation is presented. Considering a SH that hosts two people, the typical consumption profile based on the optimization problem (4.5) is presented in Figure 4.1. Represented on the Figure 4.1 are the individual consumptions of each element inside the SH (inflexible load, ESS and EV charging, smart appliances load) with the supplied price signal by the electricity retailer that was used in the optimization. This price signal varies hourly. Despite the fact that the inflexible demand must be served exactly when it is required, the other loads can be controlled by the HEMS system and can be differently allocated in order to exploit the relatively lowest price periods.

For instance, regarding the periods 10 to 11 PM a charging procedure of the ESS and the EV is noticed. This load was controlled in order to take advantage of the electricity price signal valley during these periods, as the figure indicates. A concentrated load charging to maximum profit from this price and prevent charging in higher price hours is noticed. After midnight it is expected on the typical household behavior a reduction of the inelastic load. However, the HEMS system can still profit from the relatively low prices during these periods, by allocating some load to them. However, an intensive charging of the EV is expected since it is required to be fully charged before its departure time. Still during these hours (3 and 4 AM) the HEMS system allocated the use of shiftable appliances since it happens to have a lower price in that time.

One can notice a charging process of the ESS in the periods between 9 to 11 AM. Based on this figure alone, one could reach to false conclusions, that the HEMS system is charging in a higher price signal. However, in order to further understand this behavior, one must analyze the contribution of alternative energy supplies in the SH (Figure 4.2).

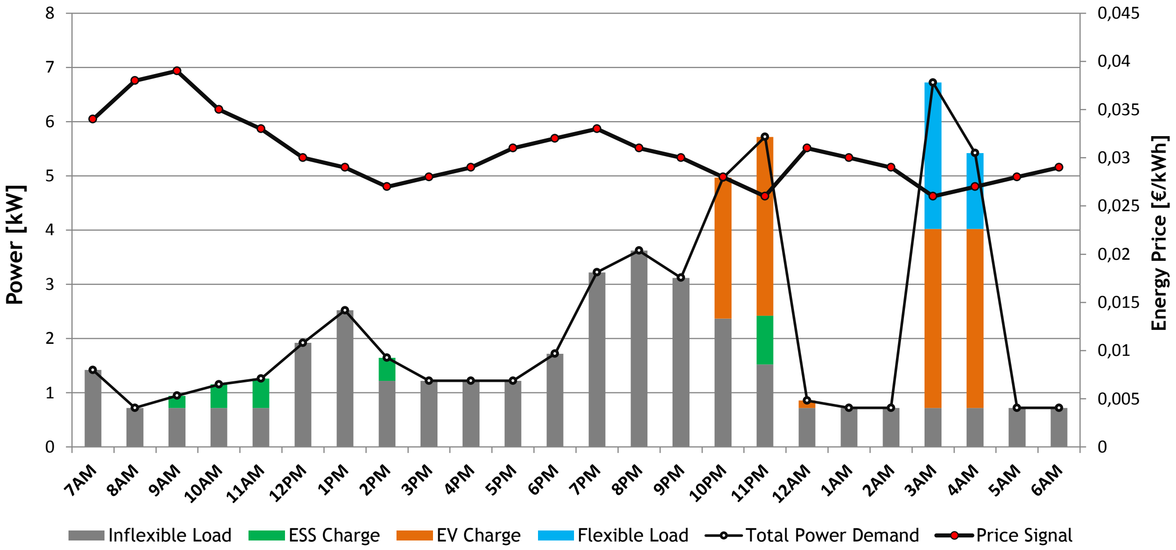


Figure 4.1: Simulation of the SH optimization: Consumption profile.

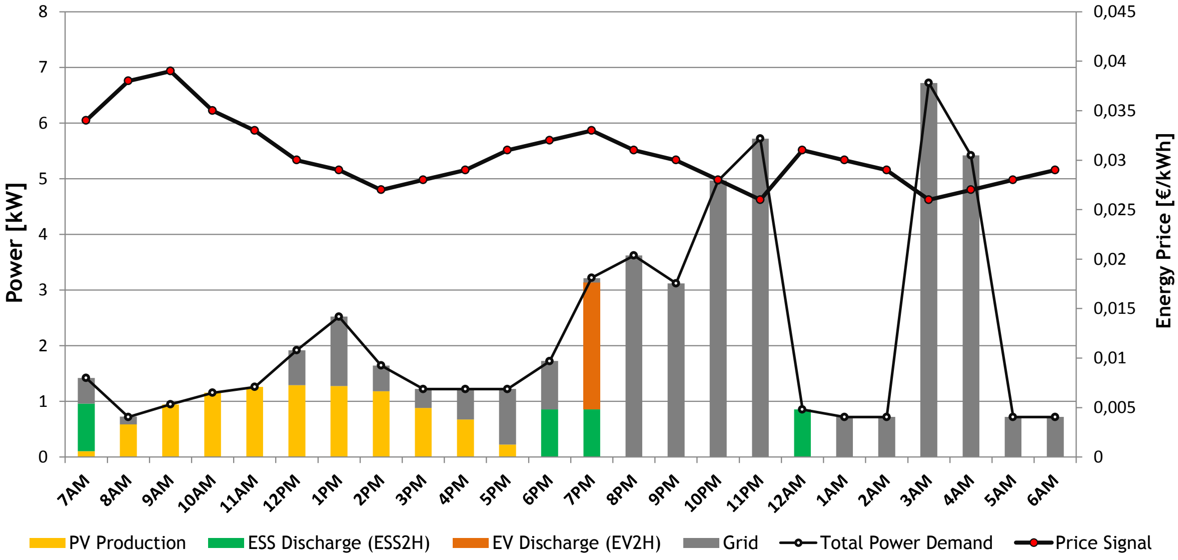


Figure 4.2: Simulation of the SH optimization: Production profile.

By analysing the smart-household power contribution, additional conclusions can be drawn. Regarding the ESS charging between 9 to 11 AM, one can conclude that the main contribution for this charging process comes directly from the solar production systems. At the beginning of SH optimization horizon (7 AM) it is noted that the main contribution from the supply came directly from the ESS system. Comparing with the previous figure (Figure 4.1), that after the ESS2H operation this energy was replaced in the following hours when the user was not at home (9 to 11 AM).

In this model the EV2H option is also available. At 7 PM, it is noticeable this contribution of the EV to supply some of the load demand by the SH. At this hour, the combined operation of the ESS2H and EV2H led to a significant reduction of the requested grid power demand. At this stage, it was the HEMS decision to coordinate the available resources to supply energy, since at that period the energy price was at a high price. This coordination action resulted in a decrease of requested power from the grid, which results in the reduction of the billing. Evidently the EV2H contribution will vary according to several conditions. A high contribution of the EV2H will only be possible if the daily driving patterns of the user are relatively low, which leads to higher SOE. Low SOEs when the EV arrives at the SH cannot contribute to the house balance since the EV needs to be fully charged before the set time of departure. Again, one can notice the ESS2H contribution at 12 AM in maintaining the inelastic load at that time.

Analysing both figures (Figure 4.1 and Figure 4.2) the full SH behavior is depicted. However, some keypoints must be noted. It is the purpose of the HEMS to guarantee the user comfort conditions as well as to ensure the optimization objective in question. It is evident that a SH will only request considerable amount of power from the DS when the price signal is at its lowest value. First point to retain is that the SH optimization will vary according to the price signal in practice. From the point of view of a DS regarding this SH, the requested power from the grid is given by Figure 4.3.

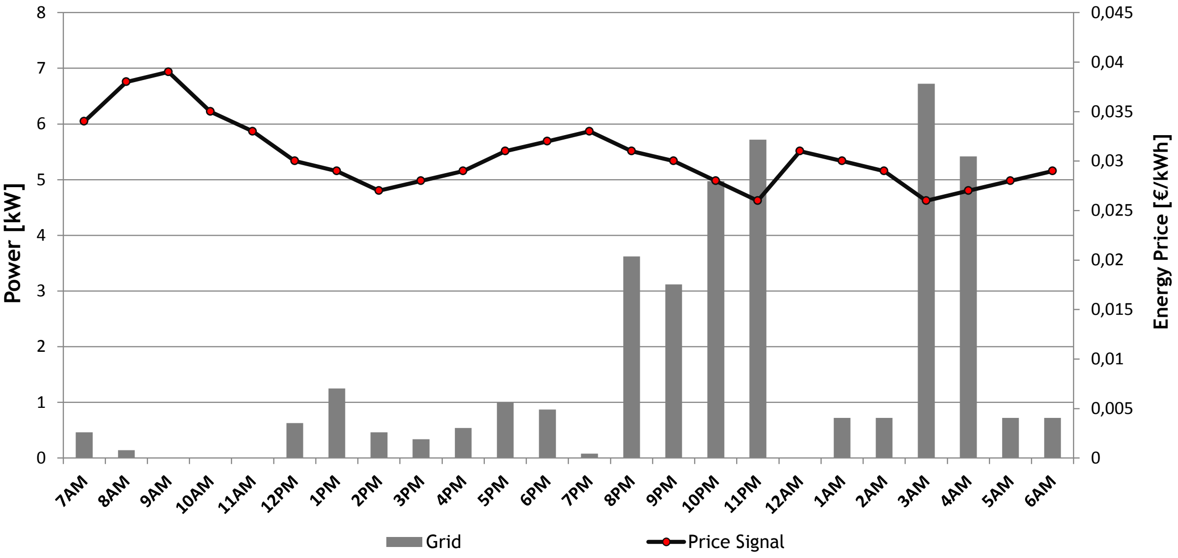


Figure 4.3: Simulation of the SH optimization: Requested power from the grid.

Analyzing the Figure 4.3, it is noted that low load amounts are allocated in the periods between 7 AM and 6 PM. One can note that at 7 PM the requested power is very low. Recalling the previously presented Figure 4.2, this happened because the main suppliers of SH energy were the EV and the ESS. However, on the next hour one can see on Figure 4.3 an increase peak of power requested from the DS, until 11 PM. Note that, from a DSO perspective this represents a rapid increase of demand in that period. Again at 12 AM, a similar behavior happens, since no power was requested from the DS. Additionally, during the low price signal at 3 AM, another peak is created for the DS. This variable power demand is a serious problem for the DS. The big differences between low and high consumption from the grid can result in an increased active power loss.

In the example presented, an expected optimization objective was demonstrated, in order to investigate the problem at hand. This optimization by the HEMS lead to the creation of two additional power peaks that were not present before. Evidently, without an HEMS this power amount would be allocated differently in hours that can have a direct user interaction, leading to concentrating even more on high demand periods. The HEMS model simulates the behavior of a rational end-user, i.e. a user that strives to strictly minimize its electricity procurement cost. Therefore, the SH flexible load is allocated based in the cost minimization purpose.

Evidently, on several occasions lower price signals will be sent at night periods in order to motivate a load shifting to those periods. However, the consequence of this action is not controlled by the DSO leaving the SH to decide on whether or not to allocate load during that period. Regarding the minimization of the cost optimization, this peak creation on a bigger scale scenario could present several problems for the DSO and the demand response objectives are not achieved.

4.3 Distribution System Model

The proposed coordination strategy aims to minimize the active power losses in the DS. It is important to know these losses in different periods, since the allocation of load from users varies with time. Therefore, the losses are calculated per branch and per time interval. Therefore, from the relation $P_{Loss} = R \cdot I^2$ one can deduce based on these considerations that the total losses (TL) are represented by equation (4.6).

$$TL = \sum_{t}^{T} \sum_{b}^{B} \left(R_b \cdot I_{b,t}^2 \right) \tag{4.6}$$

However, it is not practical to deal with current I in calculating power losses, but rather with the power P since its value typically known from the demand side. With this in mind, considering the power relation $P = V \cdot I$, and relating it to branch b at a given time t, replacing in equation (4.6) results in an approximate form of estimating the power losses given by (4.7), in which $f_{b,t}$ is the active power flow that flows on branch b in period t, and V is the nominal voltage of the DS. Notice that this approximate form considers that the voltage is constant throughout the system and that reactive power is zero, in which in practical terms it is not always possible, but the error from the approximation to the real losses are considered acceptable in practical terms. This approach would result in the same optimal topology as a complete power flow since this is determined by the direction of the flows in each branch of the DS [66], [67].

$$TL = \sum_{t}^{T} \sum_{b}^{B} \left(\frac{R_b \cdot f_{b,t}^2}{V^2} \right) \tag{4.7}$$

Despite being an approximate form, the non-linearity is present. The non-linear term $f_{b,t}$ needs to be linearized in order to ensure decent computational times for larger systems. The losses in each branch can be approximated by the equation (4.8), in which b and c are constants.

$$P_{b,t}^{loss} = b \cdot |f_{b,t}| + c \cdot f_{b,t}^2 \quad \forall b \in B, \forall t \in T \tag{4.8}$$

The power losses were linearized using the concept of Special Ordered Sets (SOS2). Being this an approximation of a non-linear function in study, its accuracy depends on the amount of samples taken from the non-linear function. More samples contribute to a more accurate representation of the function, but it comes with the expense of increased number of variables. Note that it is not required for the samples to be evenly spaced. However, one condition must be met that, at most two adjacent values can be non-zero [68].

With this concept in mind, the use of the SOS2 to approximate the flow ($f_{b,t}$) is given by:

$$\sum_{p\in P} z_{b,t,p} = 1 \ \ \forall b \in B, \forall t \in T \tag{4.9}$$

$$f_{b,t} = \sum_{p\in P} X_p \cdot z_{b,t,p} = 1 \ \ \forall b \in B, \forall t \in T \tag{4.10}$$

$$F_{b,t} = \sum_{p\in P} Y_p \cdot z_{b,t,p} = 1 \ \ \forall b \in B, \forall t \in T \tag{4.11}$$

In which z is a positive continuous variable.

In order to ensure the radial operation of the DS, a constraint must be added. A sufficient constraint is needed to ensure that no loops happen in the DS is given by equation (4.12). Since a given branch has only two possible states, a binary variable is needed to represent these decisions $y_{b,t}$. To ensure radial configuration, the total amount of closed branches must equal the difference between the total number of load nodes existent on the network N_{Total} and total number of substations N_{Sub}.

$$\sum_{b=1}^{B} y_b = N_{Total} - N_{Sub} \tag{4.12}$$

With respect to the DS nodes, a node power balance relation must be stated to ensure that the total amount of power that is being supplied to the node matches the total demand (4.13). Therefore, at a given node n in a given time t, the difference between what comes from the substation and the respected node demand $D_{n,t}$, must match the difference of incoming and outgoing flows in respect to that node. In nodes that are not substations $P^{sub}_{n,t} = 0$.

$$\underbrace{P^{sub}_{n,t} - D_{n,t}}_{\text{Net Power Balance}} = \underbrace{\sum_{b\in B: i\in\Omega^i_b} f_{b,t}}_{\text{Incoming flows}} - \underbrace{\sum_{b\in B: i\in\Omega^j_b} f_{b,t}}_{\text{Outgoing flows}} \ \ \forall n \in N, t \in T \tag{4.13}$$

The total demand at a given node $D_{n,t}$ is decomposed into two parts. First is the demand that supplies the inelastic load $P^{in}_{n,t}$ and secondly, $P^{grid}_{h,t}$ is the total power requested by the node from the DS. Is is important to separate these terms since these values will vary according to requested power quantities from each SH.

$$D_{n,t} = P^{in}_{n,t} + \sum_{h \in H^n} P^{grid}_{h,t} \; \forall n, t \tag{4.14}$$

To avoid power flow from branches that are not currently active due to reconfiguration process, the constraint (4.15) must be added. This constraint not only avoids the flow from disabled links, but also imposes a maximum power flow that each branch can support. It is considered a constant parameter and it is chosen regarding technical considerations (e.g. thermal current etc.). If the binary variable of the respecting branch b takes value 0, automatically the flow is forced to be zero.

$$-f^{max}_b \cdot y_{b,t} \leq f_{b,t} \leq f^{max}_b \cdot y_{b,t} \;\; \forall b \in B, t \in T \tag{4.15}$$

Additional DSR constraints can be generalized by (4.16), in which x_{DSO} is the vector of decision variables and S^{DSO} is the feasible region of the DSO optimization problem. Several operational constraints can be added to the DSR optimization problem. Constraints such as maximum power supply for the available substations, specifying non-reconfigurable links or any other additional constraints, that the decision-maker sees fit to include, can be added and fall under this category.

$$x_{DSO} \in S^{DSO} \tag{4.16}$$

Hence, the DSR optimization problem is summarized in equation (4.17) .

$$\begin{aligned}
\text{minimize} \quad & TL = \sum_{t}^{T} \sum_{b}^{B} \left(\frac{R_b \cdot f^2_{b,t}}{V^2} \right) \\
\text{s.t.} \quad & P^{sub}_{n,t} - D_{n,t} = \sum_{b \in B : i \in \Omega^i_b} f_{b,t} - \sum_{b \in B : i \in \Omega^j_b} f_{b,t} \;\; \forall n \in N, t \in T \\
& D_{n,t} = P^{in}_{n,t} + \sum_{h \in H^n} P^{grid}_{h,t} \; \forall n \in N, t \in T \\
& \sum_{b=1}^{B} y_b = N_{Total} - N_{Sub} \\
& -f^{max}_b \cdot y_{b,t} \leq f_{b,t} \leq f^{max}_b \cdot y_{b,t} \; \forall b \in B, t \in T \\
& x_{DSO} \in S^{DSO}
\end{aligned} \tag{4.17}$$

4.4 Power Flow Analysis Tool

The previous formulation solves the reconfiguration problem disregarding the voltage constraints on each distribution node. However, in order to verify the DS operating condition, a complete Power Flow study was used as an analysis tool. The topology that is obtained from the previous optimization problem is then set as a fixed topology in the analysis tool, in order to find out the voltage profile. In Figure 4.4 the π-model of a distribution line is depicted. According to this Figure 4.4, the active and reactive power flows, from the sending node i to the receiving node j is given by the equations (4.18) (4.19).

$$P_{i,j} = g_{ij}V_i^2 - g_{ij}V_iV_j\cos\theta_{ij} + b_{ij}V_iV_j\sin\theta_{ij} \tag{4.18}$$

$$Q_{i,j} = (b_{ij} - b_{ij}^{sh})V_i^2 - b_{ij}V_iV_j\cos\theta_{ij} - g_{ij}V_iV_j\sin\theta_{ij} \tag{4.19}$$

Following these equations, the active and reactive power balances at each node throughout the DS are:

$$\begin{aligned} P_i^{Gen} - P_i^{Load} &= \sum_{j \in i} P_{i,j} \quad \forall i \\ Q_i^{Gen} - Q_i^{Load} &= \sum_{j \in i} Q_{i,j} \quad \forall i \end{aligned} \tag{4.20}$$

In which P_i^{Gen} and Q_i^{Gen} are the total active and reactive power generated at node i, and $P_{i,j}$, $Q_{i,j}$ is the power flow from node i to every node j that is connected to i. On load nodes, also known as PQ bus, there is no generation and therefore, P_i^{Gen} and Q_i^{Gen} are set to zero, resulting in the requested load at that node matching the flows from other nodes.

The power flow problem, as the formulation indicates is a MINLP. Several works try to address this concern in order to render feasible its solution in an acceptable time. One of these strategies is to transform the problem from a MINLP into a Mixed-Integer Conic Quadratic Programming (MICQP).

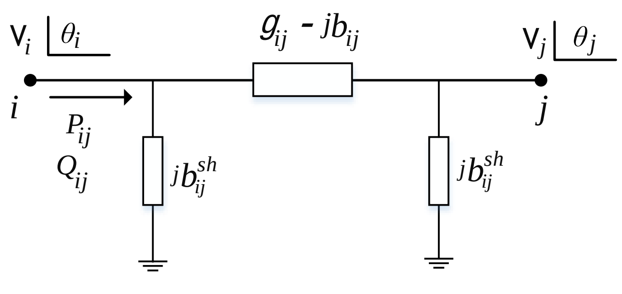


Figure 4.4: The line π-model.

In [69] a strategy was adopted by replacing the non-linear terms into additional variables that bridges the relation between the non-linear terms. Thus, the analysis tool used was based on these approximations that are described in [69]. Considering this, the assumptions that define a new set of variables are:

$$
\begin{aligned}
&U_i = V_i^2 \\
&W_{i,j} = V_i V_j \cos\theta_{ij} \\
&T_{i,j} = V_i V_j \sin\theta_{ij}
\end{aligned}
\tag{4.21}
$$

Replacing these new variables in the previous equations (4.18) and (4.19), results in a simpler linear form of expressing the flows:

$$P_{i,j} = g_{ij}U_i - g_{ij}W_{ij} + b_{ij}T_{ij} \tag{4.22}$$

$$Q_{i,j} = -b_{ij}W_{ij} - g_{ij}T_{ij} + (b_{ij} - b_{ij}^{sh})U_i \tag{4.23}$$

Additional equations must be added to ensure that no power flows through open links. This can be achieved by using the binary parameter $e_{i,j}$ that describes the status of the line ij. Note that this new variable will take the value of the previous variable y_b from the DSR optimization problem. Thus, the resulting constraints for active and reactive power are :

$$
\begin{aligned}
&-P_{max} \cdot e_{i,j} \leq P_{i,j} \leq P_{max} \cdot e_{i,j} \;\; \forall ij \in lines \\
&-Q_{max} \cdot e_{i,j} \leq Q_{i,j} \leq Q_{max} \cdot e_{i,j} \;\; \forall ij \in lines
\end{aligned}
\tag{4.24}
$$

Since its difficult to predict the expected behavior of a network, before solving its optimization, there is a need to ensure that the problem constraints are properly relaxed. This variable relaxation process assures that possible solutions are not ignored. However, this relaxation needs to be properly tweaked in several simulations to ensure that a not wider space is included in the feasible region, which could compromise the computational performance and also the ability to the problem convergence to one solution.

Therefore, in this model a relaxation technique, namely the *Big-M* was used. For example, given two variables α and β, the relaxation of this variable, according to this method would be:

$$-M \cdot (1 - z) \leq \alpha - \beta \leq M \cdot (1 - z) \tag{4.25}$$

in which M is a big enough number, to ensure a proper relaxation of the variable, and z is a binary variable. Evidently, the choice of the value of M depends on each variable that is being relaxed. With this in mind, regarding the power flow analysis, the equations that ensure a proper relaxation of the variables at play according to [69] are:

$$\begin{aligned}
&- k_{eq} \cdot (1 - e_{i,j}) \leq U_i \cdot U_j - W_{i,j}^2 - T_{i,j}^2 \leq k_{eq} \cdot (1 - e_{i,j}) \;\; \forall ij \in lines \\
&- k_W \cdot (1 - e_{i,j}) \leq W_{i,j} - W_{j,i} \leq k_W \cdot (1 - e_{i,j}) \;\; \forall ij \in lines \\
&- k_T \cdot (1 - e_{i,j}) \leq T_{i,j} + T_{j,i} \leq k_T \cdot (1 - e_{i,j}) \;\; \forall ij \in lines
\end{aligned} \tag{4.26}$$

In which k_{eq}, k_W and k_T are constants. The following equation (4.27) uses this relaxation technique to ensure that the current flowing through the line ij does not violate the maximum current limit (I_{max}) allowed for that line:

$$-k_I \cdot (1 - e_{i,j}) \leq I_{i,j}^2 \leq k_I \cdot (1 - e_{i,j}) + I_{max}^2 \cdot e_{i,j} \;\; \forall ij \in lines \tag{4.27}$$

Finally, voltage constraints are added (4.28) to ensure on the analysis tool that nodes voltage do not violate minimum (V_{min}) and maximum (V_{max}) specifications. Since one does not know the behavior of the voltage profile on high load periods (e.g EV charging periods) this constraint should be relaxed in the first runs.

$$V_{min}^2 \leq U_i \leq V_{max}^2 \;\; \forall i \tag{4.28}$$

Hence, the power flow analysis tool processes is described by equation (4.29). Note that this tool does not address the reconfiguration, but will be used to assess the benefits of the proposed strategy regarding the voltage profile of each distribution node. Therefore this tool will aid the DSO in the decision-taking, regarding the topology that was obtained previously.

$$
\begin{aligned}
\text{minimize} \quad & \sum_{i}^{N_{Sub}} \sum_{j \in i} P_{i,j} \\
\\
\text{s.t.} \quad & P_i^{Gen} - P_i^{Load} = \sum_{j \in i} P_{i,j} \quad \forall i \\
& Q_i^{Gen} - Q_i^{Load} = \sum_{j \in i} Q_{i,j} \quad \forall i \\
\\
& P_{i,j} = g_{ij} U_i - g_{ij} W_{ij} + b_{ij} T_{ij} \\
& Q_{i,j} = -b_{ij} W_{ij} - g_{ij} T_{ij} + (b_{ij} - b_{ij}^{sh}) U_i \\
\\
& -P_{max} \cdot e_{i,j} \leq P_{i,j} \leq P_{max} \cdot e_{i,j} \quad \forall ij \in lines \\
& -Q_{max} \cdot e_{i,j} \leq Q_{i,j} \leq Q_{max} \cdot e_{i,j} \quad \forall ij \in lines \\
\\
& V_{min}^2 \leq U_i \leq V_{max}^2 \quad \forall i \\
\\
& -k_I \cdot (1 - e_{i,j}) \leq I_{i,j}^2 \leq k_I \cdot (1 - e_{i,j}) + I_{max}^2 \cdot e_{i,j} \quad \forall ij \in lines \\
\\
& -k_{eq} \cdot (1 - e_{i,j}) \leq U_i \cdot U_j - W_{i,j}^2 - T_{i,j}^2 \leq k_{eq} \cdot (1 - e_{i,j}) \quad \forall ij \in lines \\
& -k_W \cdot (1 - e_{i,j}) \leq W_{i,j} - W_{j,i} \leq k_W \cdot (1 - e_{i,j}) \quad \forall ij \in lines \\
& -k_T \cdot (1 - e_{i,j}) \leq T_{i,j} + T_{j,i} \leq k_T \cdot (1 - e_{i,j}) \quad \forall ij \in lines
\end{aligned}
\tag{4.29}
$$

4.5 Coordination Strategy

The literature survey demonstrated an existent gap in the field of DSR combined with DR. Several studies exist, on addressing the benefits of a well coordinated DR strategy. However, none of these studies addressed the benefits of developing a strategy that combines a demand response strategy with a reconfiguration strategy from the DSO point of view.

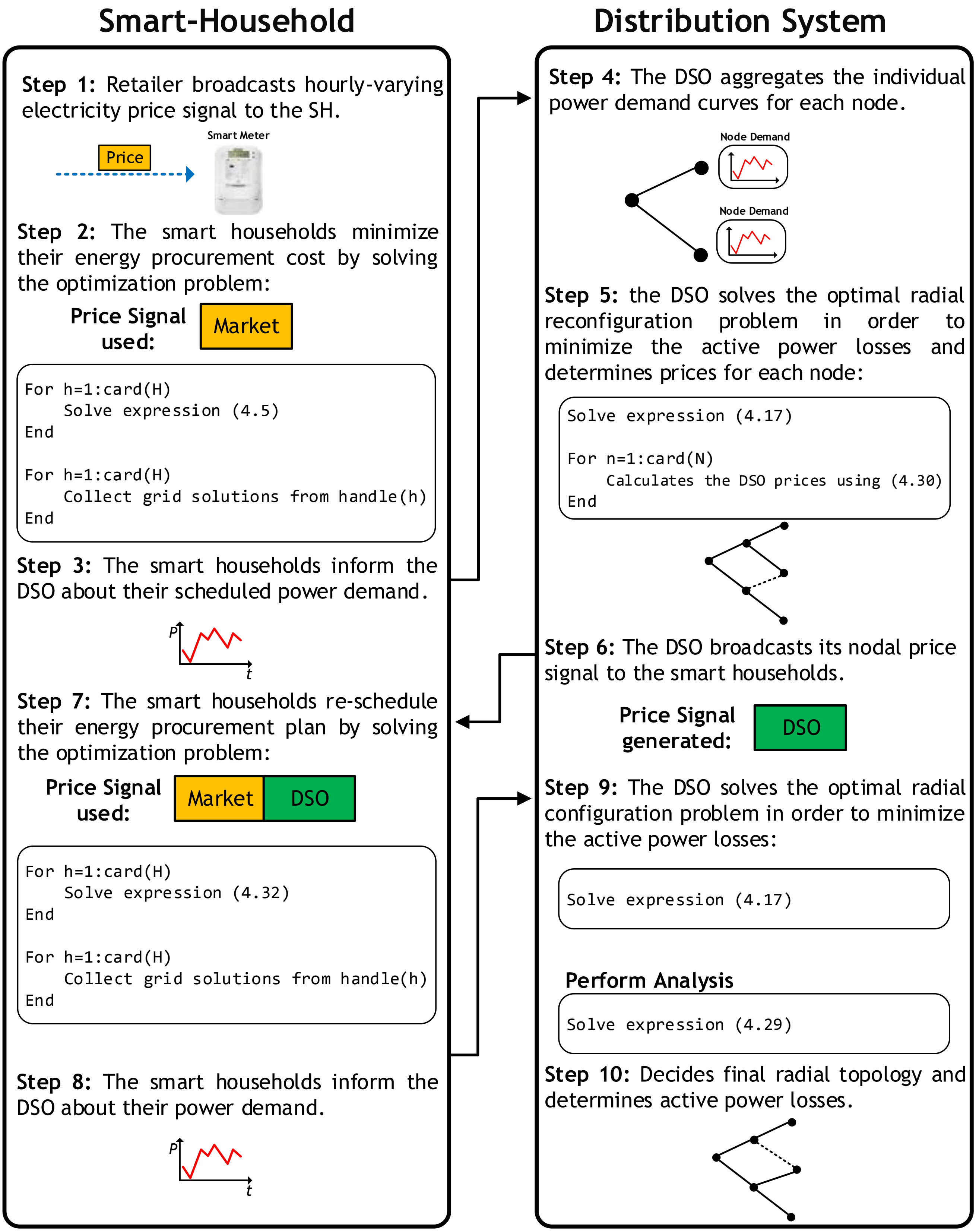
Tariff systems will, at some point, motivate the users to shift their load to a low price period. It is even expected that, with the increase of home automation systems, the end-user would not need the direct interaction to perform load shifting since this procedure is done automatically by the HEMS. Depending on the desired objective of each user, the HEMS will take its decisions while guaranteeing the user comfort. The tariff system based on RTP, according to the presented literature survey, seems to be the most promising mechanism since it represents the actual production price in each period.

Pricing the consumers with RTP prices could create a problem for the DSO regarding the losses. The RTP will indirectly motivate the price responsive users, to shift their loads to relatively lower price periods. If the users exploit the pricing curve by allocating their shiftable loads, to low price periods, new network load peaks could occur in hours that were not existent before, and one of the objectives of demand response is not achieved, the flattening of load curve.

It is important that the pricing mechanisms address not only economical concerns on production, but also the technical concerns of the electrical DS. This model proposes a new strategy to motive the demand response, by introducing the DSO input in generating a price signal, which will be taken into account in decision-making process taken by the user. Therefore, this interaction will assume two distinct sides, the DSO and the end-user. In Figure 4.5 the proposed coordination strategy is presented.

The proposed coordination strategy starts with **Step 1**, in which the users receive the electricity price signal through the smart-meter. For the purpose of this work, it is assumed that the users receive 24-Hour price signal based on the day-ahead prices, well before the actual dispatch day (e.g. the previous evening). The prices of the market may change during the real-time operation of the system but the consumers will be priced according to the determined day-ahead prices. This is a common practice, e.g. in MISO market [70].

In **Step 2**, each SH solves its optimization problem. In practice, each SH will solve a different problem regarding their comfort specifications. It is assumed that the optimization problem done by one individual (one SH) is the same to every SH present in the DS, which are responsive to the incentives provided through the dynamic price signal. In this step, advanced computation capabilities will be exploited in order to make it feasible in an acceptable time frame for practical applications as it will be explained in Section 4.6.



Step 1: Retailer broadcasts hourly-varying electricity price signal to the SH.

Step 2: The smart households minimize their energy procurement cost by solving the optimization problem:

```
For h=1:card(H)
    Solve expression (4.5)
End

For h=1:card(H)
    Collect grid solutions from handle(h)
End
```

Step 3: The smart households inform the DSO about their scheduled power demand.

Step 7: The smart households re-schedule their energy procurement plan by solving the optimization problem:

```
For h=1:card(H)
    Solve expression (4.32)
End

For h=1:card(H)
    Collect grid solutions from handle(h)
End
```

Step 8: The smart households inform the DSO about their power demand.

Step 4: The DSO aggregates the individual power demand curves for each node.

Step 5: the DSO solves the optimal radial reconfiguration problem in order to minimize the active power losses and determines prices for each node:

```
Solve expression (4.17)

For n=1:card(N)
    Calculates the DSO prices using (4.30)
End
```

Step 6: The DSO broadcasts its nodal price signal to the smart households.

Step 9: The DSO solves the optimal radial configuration problem in order to minimize the active power losses:

```
Solve expression (4.17)
```

Perform Analysis

```
Solve expression (4.29)
```

Step 10: Decides final radial topology and determines active power losses.

Figure 4.5: Proposed coordination strategy.

In **Step 3**, after the optimization process, each smart household communicates its scheduled power demand to the DSO, through the existent communication infrastructure.

In **Step 4**, since it is impractical for the DSO to known each individual household load schedule, the DSO aggregates their load according to the corresponding node that each smart house belongs. In this stage the DSO can have a network profile for each distribution node and its corresponding load demand.

In **Step 5** the DSO knows the corresponding load scheduling curve per node in the DS. In this stage, the DSO solves its optimization problem regarding network reconfiguration in order to minimize the active power losses. This reconfiguration guarantees that the DSO operates with the least losses possible for the corresponding load curve per node, which is a result of the communicated demand per user. After the reconfiguration process is done, the DSO generates its prices in order to further motivate the users into altering their consumption patterns. This signal approach tries to balance the low price signals that are provided by the market retailer, which the SH could exploit leading to creating an additional network load peak. After the SH solve their optimization and based on their load scheduling, the DSO generates a price signal per period if the communicated load demand is not acceptable by the DSO. If not, the DSO generates a penalty price to try to demotivate the SH owners to shift into hours more suitable for the DSO. In order to guarantee a good balance in each distribution node, the pricing signal matches its corresponding node. Since the marginal cost of the system losses are difficult to quantify, the adopted method is described by the equation (4.30). The generated DSO price μ_t^n is designed by charging the unitary increase of demand with respect to their contribution to the losses in each node. This DSO pricing scheme follows a similar logic that is presented in [71].

$$\mu_t^n = \frac{\left(1 + \frac{\partial TL}{\partial D_{n,t}}\right) \cdot \sum_{h \in H^n} P_{h,t}^{grid} \cdot \lambda_t^{buy}}{TL} \quad \forall n, t \tag{4.30}$$

After the generation of these prices the DSO informs the end-user, through the communication infrastructure, the new addition to the pricing signal (**Step 6**).

In **Step 7** the smart households are now aware of the new prices provided by the DSO and also aware of the previous pricing signal provided by the market retailer. At this stage the smart households repeat their optimization problem regarding both pricing signals (Retailer and DSO). This optimization is done in order to ensure that each smart household has the optimal least cost operation regarding the new prices. Therefore, the new objective function that describes the total cost of each SH is given by equation (4.31). Note that this new objective includes two prices: the previous price from the original price signal λ_t^{buy} and the new price generated by the DSO μ_t^n. This new price is applied to the difference of power that the SH requests now compared with the previous request.

$$TC_h = \sum_t \left\{ [P_{h,t}^{grid} \cdot \lambda_t^{buy} + \mu_t^n \cdot (P_{h,t}^{grid} - P_{h,t}^{grid,prev})] \cdot \Delta T \right\} \tag{4.31}$$

By replacing this new objective function (4.31) in the previous optimization problem (4.5) the new optimization problem of each SH at this stage is given by:

$$
\begin{aligned}
\text{minimize} \quad & TC_h = \sum_t \left\{ [P_{h,t}^{grid} \cdot \lambda_t^{buy} + \mu_t^n \cdot (P_{h,t}^{grid} - P_{h,t}^{grid,prev})] \cdot \Delta T \right\} \\
\text{s.t.} \quad & x_{PV} \in S^{PV} \in S^h \\
& x_{SA} \in S^{SA} \subset S^h \\
& x_{EV} \in S^{EV} \subset S^h \\
& x_{ESS} \in S^{ESS} \subset S^h \\
& P_{h,t}^{grid} + P_{h,t}^{EV2H} + P_{h,t}^{ESS2H} + P_{h,t}^{PV} = \\
& P_{h,t}^{in} + P_{h,t}^{EV,ch} + P_{h,t}^{ESS,ch} + \sum_{m \in M^h} P_{m,h,t}^{A} \; \forall t
\end{aligned}
\tag{4.32}
$$

In **Step 8** each SH communicates the new load demand schedule to the DSO. It is possible at this stage that the load demand differs from the previous communicated demand, since it is now exposed to two price signals. After the communicated load schedule to the DSO, the interaction from the smart-household side is terminated.

In **Step 9** the DSO knows the new aggregated load in each distribution node, and resolves its optimization problem regarding the new load demand schedule. After the optimization terminates, the DSO could have two reconfiguration scenarios options to compare, before and after the new generated price signal. The decision-maker in the DSO side, with the presented topologies and its possible outcomes, decides the final operating topology (**Step 10**).

4.6 Computational Optimization

In the previous chapters, the importance of achieving a solution within an acceptable time frame has been highlighted. Complex models tend to present an increased computational burden when they are applied to large-scale systems. Lack of computational efficiency may prove a demotivating factor as regards their practical application. Thus, there is a need to investigate the potential of exploiting modern computing techniques in order to improve the computational efficiency and motivate the decision-makers to adopt such tools.

In the practical side of the proposed interaction framework, each smart-household will solve its optimization problem individually regarding its own SH domain. Basically each optimization problem is solved by the SH owner and the desired load schedule is then reported to the DSO. This leaves the computational burden of the SH optimization model to the HEMS system that each SH contains.

However, it is important that the DSO can predict certain times the behavior of the consumers, by analyzing their response to price change. Given this proposed coordination strategy, it is not expected that the DSO can accurately forecast the load schedule without running a similar optimization problem that is being done by each individual user. By being aware of an expected behavior from the users, the DSO can use this information with the addition of the reported information from the users, to design better incentives and select its best operation topology for the DS in its current condition.

The proposed model was implemented using the optimization software GAMS [72]. Additionally, to address this computational concern, the GAMS Grid Computing capabilities were explored. With the current improvements in hardware, multi-processor computers are becoming widely available. However, the current methods of solving the optimization problems leave the optimization platforms under-utilized in comparison with their available resources. A comparison of solving approaches can be seen in Figure 4.6.

The default solving approach (synchronous solving), starts by generating the model based on the available data and the equations that participate on the model to be submitted to a solving stage. In this stage, the model is solved, ending this stage when a better solution is found. This stage is a time varying process and depends on the model complexity. After the end of this stage the solutions are reported.

By using the proposed and improved grid approach, the software can take advantage of models that can be decomposed and solved separately, such as the optimization problem of the SH presented in (4.1), which leads to better use of the multiple CPUs available in the workstation. This approach, also considered as an asynchronous approach, envisions the decomposition of the optimization problem into several sub-problems in order to be solved separately by each individual CPU. These sub-problem blocks can be solved in parallel mode, without requiring the full solving of the entire model. When a processing unit finishes with solving its sub-problem block, automatically stores locally the solution from that block and immediately takes the next subproblem block, if exists. After all solution blocks have been stored, a collection loop retrieves the solutions and displays the optimal solution found.

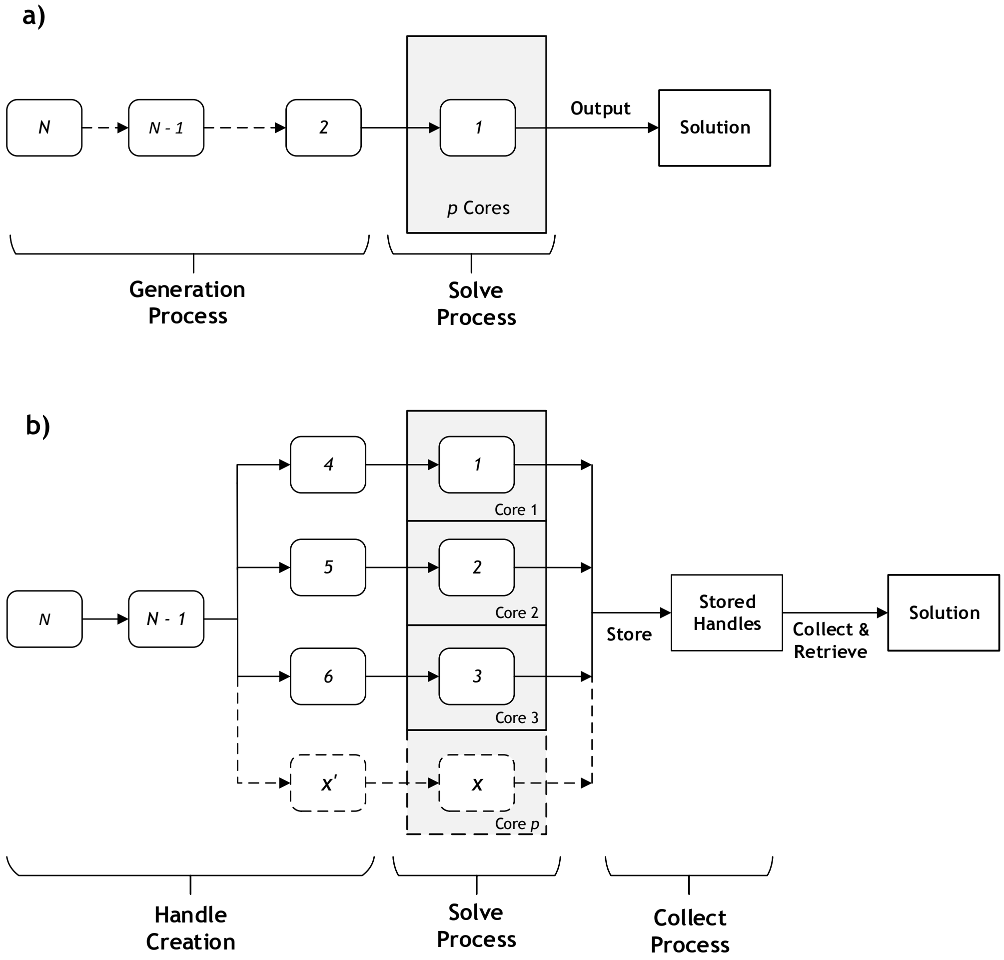


Figure 4.6: Computing approaches: a) Default Solving, b) Grid Solving.

With this technique, each sub-problem block can be solved separately exploiting the full capacity of the multi-processors, preventing the low use of memory and idling CPUs from the default solving approach. It is important to state that not every optimization problem can be decomposed, due to its nature. Additionally, several modifications must be added to the original optimization model to enable the grid approach. Still, it has significant advantages that cannot be neglected, especially in repeated tasks and large iteration loops, thus being applied in the novel coordination framework, regarding the SH optimization.

4.7 Summary

In this chapter a SH model was explained in order to demonstrate the problems faced by the DSO. Afterwards, the optimization problem to be done by the DSO and the power flow analysis tool used to verify the DS behavior was presented. Then, the novel coordination model framework was presented, ending the chapter with the adopted computational methods that were used in this work, namely grid computing.

Chapter 5

Results and Discussion

> *"Difficulties mastered are opportunities won."*
>
> WINSTON CHURCHILL

5.1 Introduction

In this chapter the results from the proposed coordination strategy are presented. It starts by presenting the data input used in the SH optimization problem. Later, two test DS on 16-Bus and a 33-Bus will be presented, depicting the relevant information on the simulations while discussing results relevant to the coordination strategy.

On the 16-Bus DS the conceptual working principle of the proposed coordination strategy will be presented. It will highlight the basic principles that this novel coordination strategy will try to accomplish. This is presented in this conceptual system that is a typical test system used to demonstrate benefits of strategies in DS.

Later, a more detailed analysis will be presented for a larger 33-Bus DS. The detailed analysis is only presented in this system, since this system structure is closer to practical DS. This system will allow demonstrating the benefits of the proposed strategy in larger systems.

5.2 Smart-Household Data Input

In this section, the data input regarding the SH optimization are presented. These data is built under several assumptions that are presented. The first consideration taken is the data regarding the SH consumptions. The SH consumption is decomposed into two parts: Flexible load and Inflexible load.

As it was presented before, the flexible loads are the loads that can be controlled by the HEMS system in order to fulfill the desired objective function, minimization of the electrical bill. However, these SH also have loads that can not be controlled but need to be quantified, the inflexible load. For the SH load profiles, two types of families were considered in this work (2 and 4 occupants).

The load profiles were built taking into account typical power ratings of existing appliances from an existent SH [73]. Therefore, the inflexible load profiles are depicted in Figure 5.2.

For the purpose of this work, two load profiles were considered, one for each test case (16-Bus and 33-Bus DS), and are presented in the Figure 5.2.

Since the arrival times are not always known and depend on each user driving patterns, it is considered that this follows a normal distribution with mean at 5 PM and a standard deviation of 2 hours, being truncated at 12 PM and 10 PM to consider an expected arrival behavior. This arrival time distribution was created using real data taken from [74]. For the purposes of this work, it was considered that all the EVS must be fully charged before the time of departure at 6 AM. It is also considered in this study, that each SH have an ESS system with an energy capacity of 3 kWh. The initial SOE of the ESS system follows a normal distribution, which was created considering a mean capacity at 40 % with a standard deviation of 10%. To ensure minimum and maximum specifications, this distribution was truncated at lower bound 25% and upper bound 70%. For each SH participating in the demand response, it is assumed that it has a PV system installed. It is considered that the installed PV capacity is of 1 kW for the 2 occupants family and 1,5 kW for the 4 occupants family. In Figure 5.1 the normalized PV production, per kW of production, is presented.

The price signal considered for this optimization is illustrated in Figure 5.3. The users receive this price signal from the market retailer. As it was presented before, it is assumed that this price is based on the day-ahead prices that they receive before the optimization day. Users will be priced according to this price signal, having guarantees that it does not change during the day of the optimization [70].

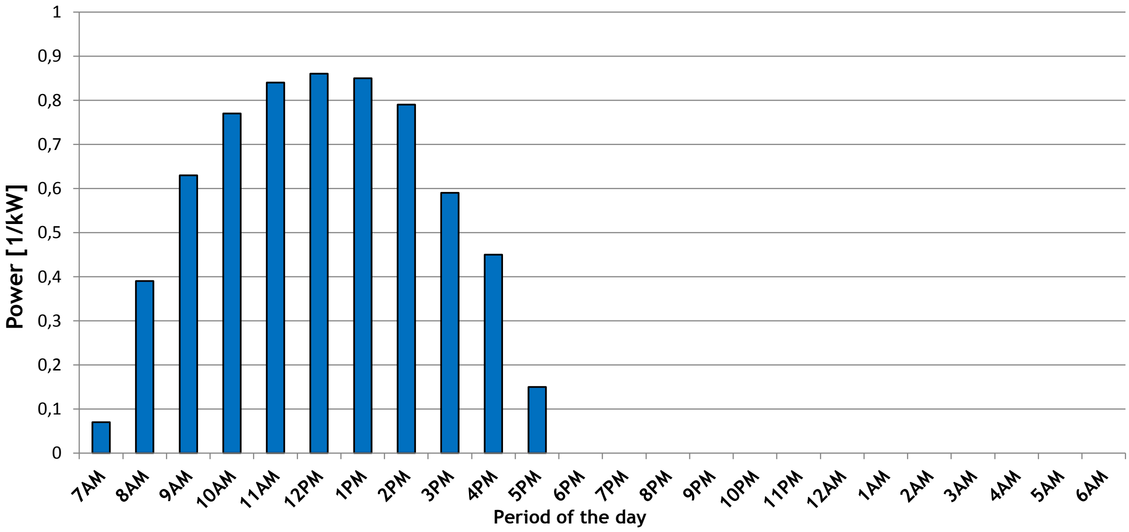


Figure 5.1: Normalized PV production.

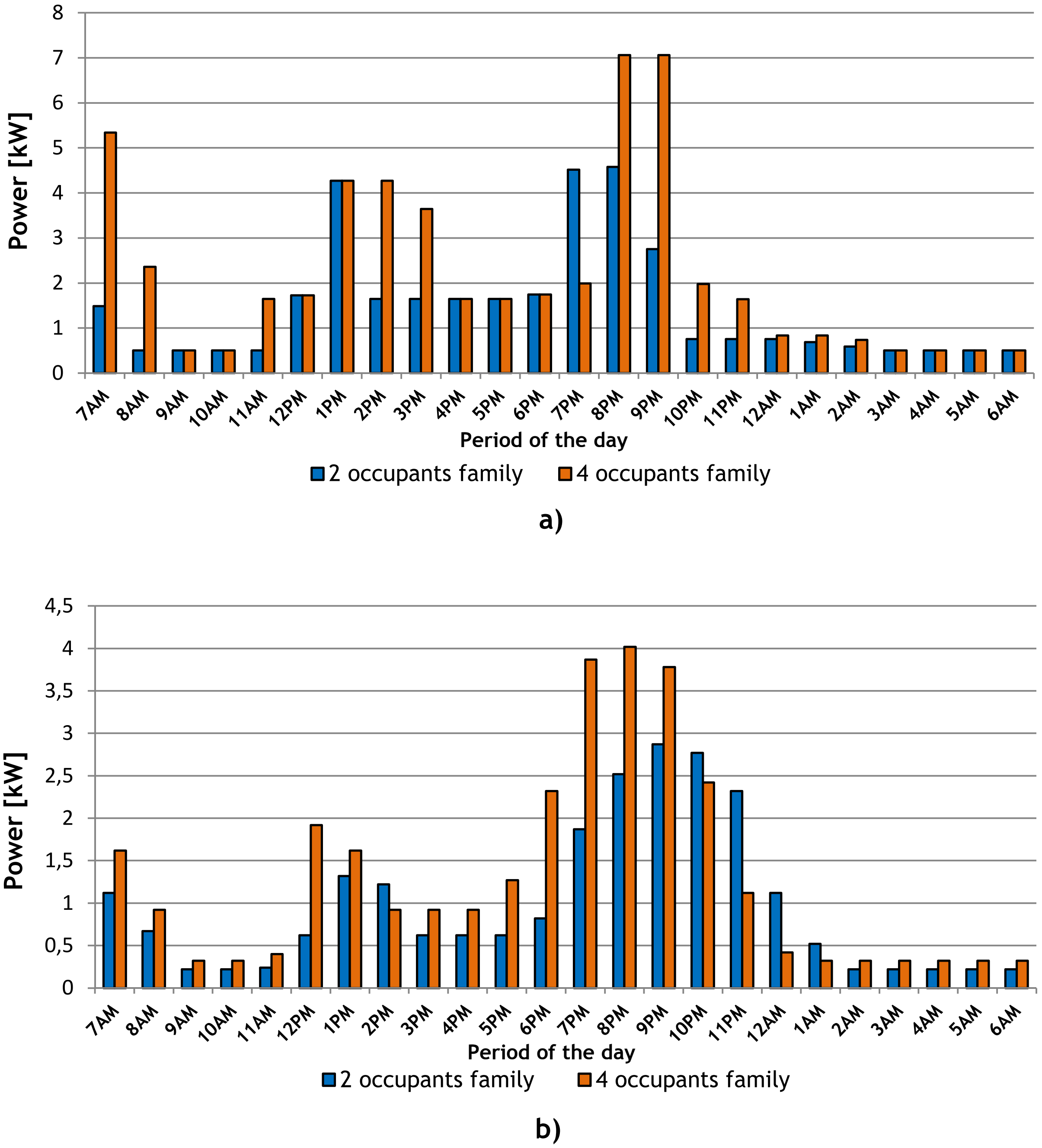


Figure 5.2: The Smart-Household inflexible load profiles used in the 16-Bus (a) and in the 33-Bus (b) DS.

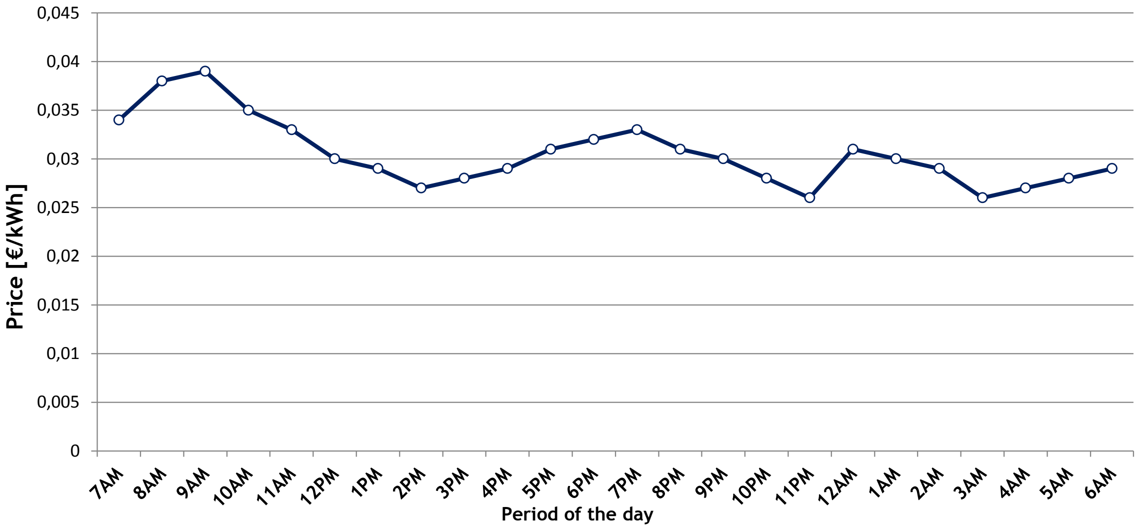


Figure 5.3: The 24-Hour varying electricity price signal.

5.3 Test case: Modified 16-Bus Distribution System

The first test case presented is based on a modified version of a 23 kV 16-bus Distribution System [75]. The system is depicted in Figure 5.4, which consists in only one substation, unlike the original system that has three substations. For this system the initial operation state, before reconfiguration, considers that branches 3-9, 8-12 and 5-14 are normally open branches.

Based on this system and its data [75], some assumptions were made. In order to study the behavior of the SH in relation with the coordination scheme, it was assumed that each 1 MW of the system load represents approximately 400 clients.

Additionally, it was considered that 25 % of the total number of clients in a node are price responsive, meaning that they have an HEMS and respond to the time-varying price signal. Therefore the data referring to this system that represents the total number of users and responsive users are shown in Table 5.1.

Recall that this DS is a conceptual test system, which is only presented here to demonstrate the working principles and the objectives of the proposed strategy. It is considered a small system, becoming easier to study the behavior of the strategy under the influence of low number of clients.

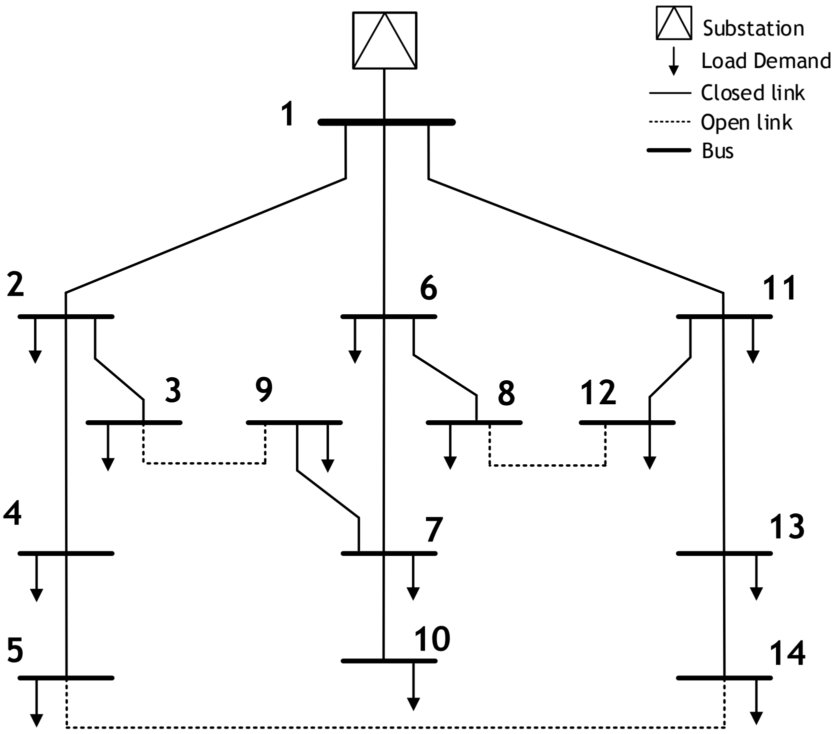


Figure 5.4: Modified 16-Bus Distribution System.

Table 5.1: Number of clients at each node in the modified 16-Bus DS.

Node	Number of clients	Non-responsive clients	Number of smart households
1	----	----	----
2	800	600	200
3	1200	900	300
4	800	600	200
5	600	450	150
6	1600	1200	400
7	2000	1500	500
8	400	300	100
9	240	180	60
10	1800	1350	450
11	400	300	100
12	400	300	100
13	400	300	100
14	840	630	210

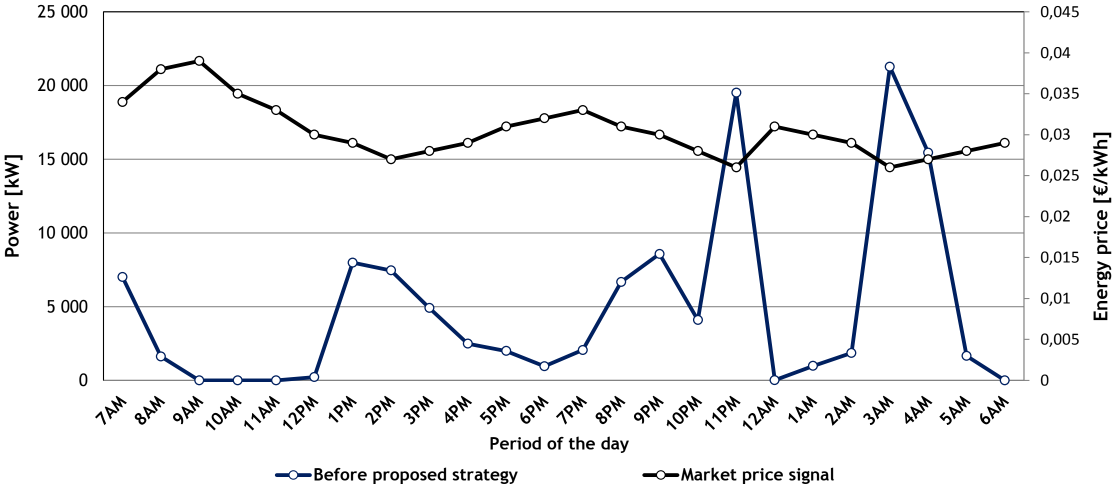


Figure 5.5: Total power request of SH from the grid (Step 1 of the optimization).

The coordination interaction starts by the SH optimization process as it was explained before. The purpose is the minimization of the electrical bill. Based on the data presented and the desired objective function, it is needed to study the impact of the strategy on the DS. In Figure 5.5 the total power request from the DS is presented. The SH will always try to exploit the market retailer price signal, in order to benefit from it by only demanding the power from the DS if needed.

Evidently, the SH have several resources at their disposal that can cover their demand. In the Figure 5.5 one can notice this behavior by checking periods such as 9 AM to 1 AM that it has no power request. This is possible due to the PV production that each SH contains. Additionally, at 12 AM one can notice the demand being non-existent at that period. Since the price signal provided by the market retailer at this period is relatively high, it is expected that at this period the total load demand of the SH was provided by the ESS2H and EV2H capabilities that each SH have.

Note that the presented curve only depicts the SH power request from the DS (Figure 5.5). At this stage the DSO knows the required load that is from the inflexible load of the system, the non-responsive users and the total load that is demanded from the responsive users. It is to these clients that the DSO generates a new price signal in order to induce a new shift of loads that were allocated in periods that constitutes considerable losses for the DS.

Therefore, in Figure 5.6 the generated price signals per node are illustrated. Note that this price signal must be generated for each node for an evident reason. For instance, an individual signal for each node allows the DS to have better control over the expected response behavior, by designing more appealing signals to extreme load condition nodes. In this work, the generation price mechanism is built on the principles that prices the losses according to each node contribution to its loss increase. By analysing Figure 5.6 some conclusions can be drawn. It is noted that nodes that posses more responsive clients receive higher price signals.

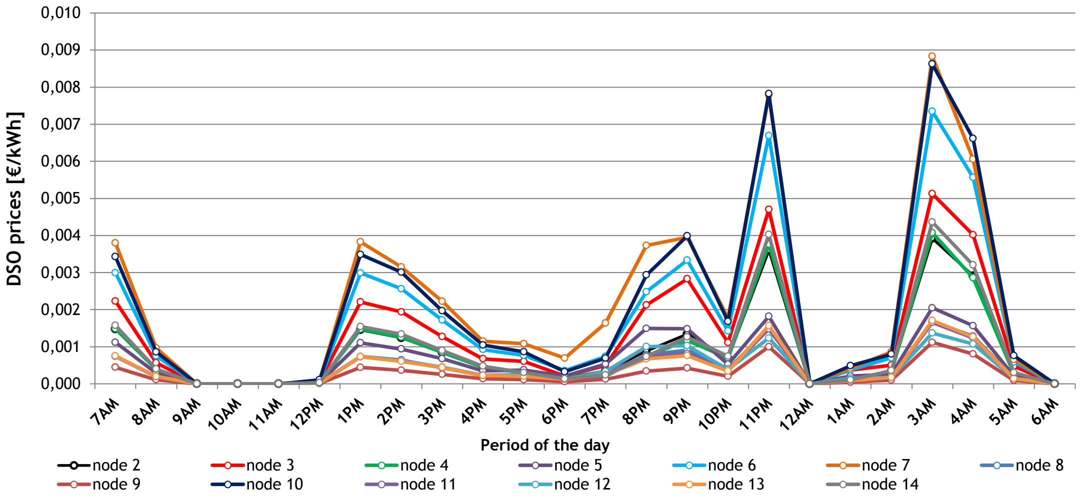


Figure 5.6: Price generation from the DSO to each node in the modified 16-Bus DS.

This is an expected behavior since the number of resources available to the SH increase and with it their impact on the DS. Moreover, it is not only the number of users that needs to be considered. Nodes such as node 10, based on the topology presented in Figure 5.4 even with reconfiguration, is still an end node (antenna connection). Together with the fact of having high demand from the SH and the other inflexible system load, leads to increased losses on the branch that connects node 10.

Additionally, a similar adverse behavior can be noticed from nodes of lesser demand. Considering the generated price signals, it is observed that nodes with small contribution to the system losses, such as node 9, have the lowest price signal received from the DSO. This is an expected behavior since 60 clients in a total of 240 clients that exist on that node do not bring increased losses when compared to more crowded nodes.

Therefore, in Figure 5.7 the DSO price signals relation in comparison with the supplied price signal from the market retailer is illustrated. After receiving these new prices the SH have now to consider two price signals in the optimization problem as it was described before in Figure 4.5.

In Figure 5.8 the comparison of the grid power request (before and after the proposed strategy) is presented. By analysing the SH energy demand from the grid, several conclusions can be drawn. First noticeable point of the proposed strategy was the mitigation of two significant network peaks that were existent previously, the periods of 11 PM and 3 to 4 AM. These peaks were mainly caused by the EV charging at these hours since the HEMS exploited the ability of charging them at a lower market retailer price signal. By introducing the new price signal as it was depicted before in Figure 5.7, changed the allocation of these vehicles. With the intensified charging of EVs, these network peaks increased significantly their contribution to the DS losses.

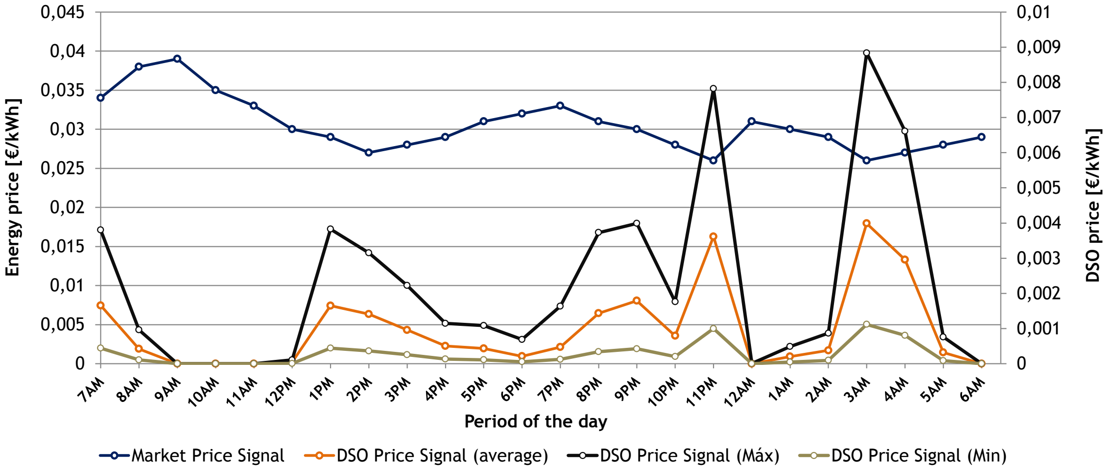


Figure 5.7: Price signals comparison at each DS node in the modified 16-Bus DS.

The DSO generated a signal that envisioned an increased price at these periods in order to demotivate the intensified allocation of these vehicles at these hours. As it is depicted in Figure 5.8 these peaks ceased to exist by allocating this load to different hours. For instance, a new peak that was created with the proposed strategy happened at 5 AM, being expected that some EV charging happened in this period.

Additional benefits can be observed in Figure 5.8. For instance, the contribution of the proposed strategy in valley filling, the most notably at 10 PM. In this period, the use of the proposed strategy led to an increase of the SH power requested from the DS. Before the proposed strategy, this period (10 PM) had low demand following a high demand in the next period (11 PM). With the proposed strategy this difference of power demand (10 PM and 11 PM) was significantly reduced, which is beneficial for the DS.

It is clear by analyzing Figure 5.8 that the new DSO price was considered in the optimization of the SH. The low price signal allowed the SH to reconsider how they properly allocated their load by exploiting the DSO benefits at that period. This allowed them to allocate some load at that period to contribute to the valley filling purposes of the DSO.

Moreover, this contribution to less loaded periods is noticeable such as night periods between 12 AM and 4 AM. At this period it allowed a smoother energy request from the DS. Moreover, between 1 PM and 7 PM a moderate increase of the requested energy occurred. This allowed the DSO the purpose of gradually filling the low demand periods and also preventing high peak demand periods that were caused from the SH optimization procedures.

Before considering the reconfiguration of the DS a simulation was made in order to demonstrate the benefits of the proposed strategy in a fixed default topology. The results presented before were relevant in considering the use of reconfiguration. Therefore, the overview of the results is presented in Table 5.2.

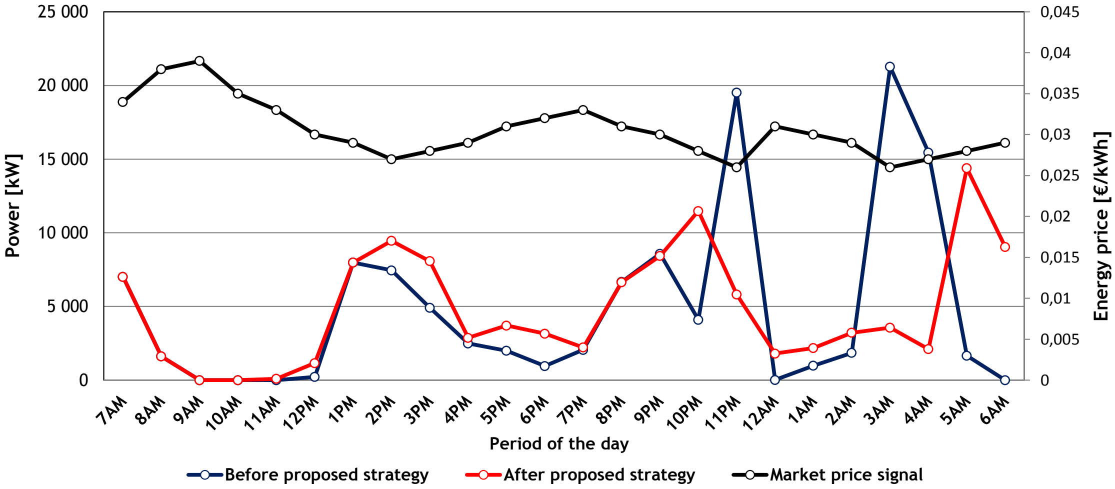


Figure 5.8: Total power request of the SH from grid in the modified 16-Bus DS.

Considering the base test of no coordination strategy and without reconfiguration, the total active losses of the system were 12,249 MWh. Based on the results, the benefits of adopting reconfiguration strategies are clear, contributing to a significant loss saving. Moreover, the use of the proposed strategy, combined with the reconfiguration capabilities, allowed the DSO to reduce the overall system losses, to a value of 10,634 MWh.

The proposed strategy with reconfiguration achieved a reduction of 13,2 % when compared to the base test (fixed topology without proposed strategy). By only adopting reconfiguration without the proposed strategy the loss reduction is 7,5 %. It is evident that the use of this strategy can increase the DS loss savings. By adopting the proposed strategy, the losses can further decrease (around 5,7 %) comparatively to the reconfiguration without strategy.

An additional benefit of the proposed strategy can be seen using the metric peak-to-average ratio. This can be studied by analysing the maximum network peak created from the request of energy of the SH from the DS, over the average energy requested during the day. Considering the proposed strategy only in the test cases that involve reconfiguration, the peak-to-average ratio decreased from 4,37 to 2,98.

Table 5.2: Active power losses for the modified 16-Bus DS.

	Without Reconfiguration	**With Reconfiguration**
Without Novel Coordination Strategy	12,249 MWh	11,334 MWh
With Novel Coordination Strategy	11,467 MWh	10,634 MWh

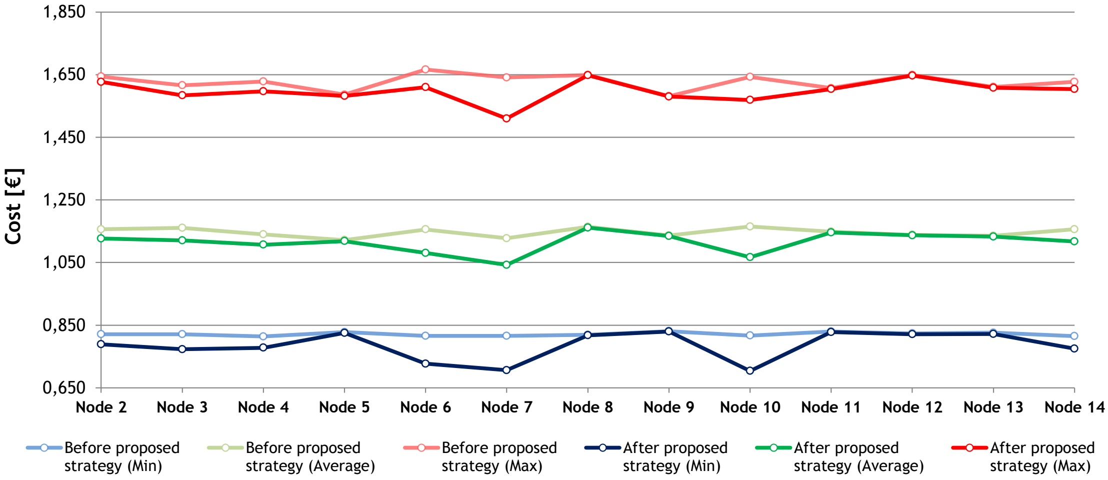


Figure 5.9: Aggregated Smart-Households cost comparison per node in the modified 16-Bus DS.

The benefits of the proposed strategy for the DS are evident. However, a major point needs to be addressed: the costs that result from the SH optimization. This strategy could raise concerns as regards the compromise of the economic benefits that would motivate end-users to enroll under time-varying pricing schemes. Therefore, in Figure 5.9 the relation of the paid prices per day of the aggregated SH per node (before and after the proposed coordination strategy) is presented.

It is evident that, with the use of the proposed strategy the SH can benefit in their optimization. For instance, previously the minimum price that at each node was paid was around 82 cents. With the provided electricity price, it is extremely difficult that a better optimization can be done by the SH. With the proposed strategy it is noticeable that at some nodes, at least one SH benefit from the provided DSO price, lowering the minimum payment at some nodes.

Moreover, the reduction of the average payment before and after the coordination strategy is evident. Additionally, it is also evident that not all nodes share the same benefits. Even at some nodes the SH cost balance remained the same. However, on other nodes a significant benefit occurs with the proposed strategy (e.g Nodes 6, 7 and 10).

When studying this behavior regarding the data provided in Table 5.1, these nodes represent the nodes with more responsive users. Evidently, the SH that belong to these nodes represent a bigger flexible load that most contributes to the loss of the system. Especially at these nodes, the price generated by the DSO motivates them to alter their consumption behaviors, leading to lowering their prices. On nodes that contribute less to the DS losses, the price generated by the DSO has no significant role in altering their consumption.

It was stated before that the DSO would have the possibility after the proposed strategy of changing the network topology in two instances. The first reconfiguration approach starts when the DSO receive the aggregated load signal from the optimization of the SH. At this stage the DSO can perform a reconfiguration based on that signal. After sending the signal to the SH to perform its re-optimization, the DSO based on the new aggregated load could have the possibility of reconfiguring again. The final configuration of the DS that achieves the minimum active power losses is depicted in Figure 5.10.

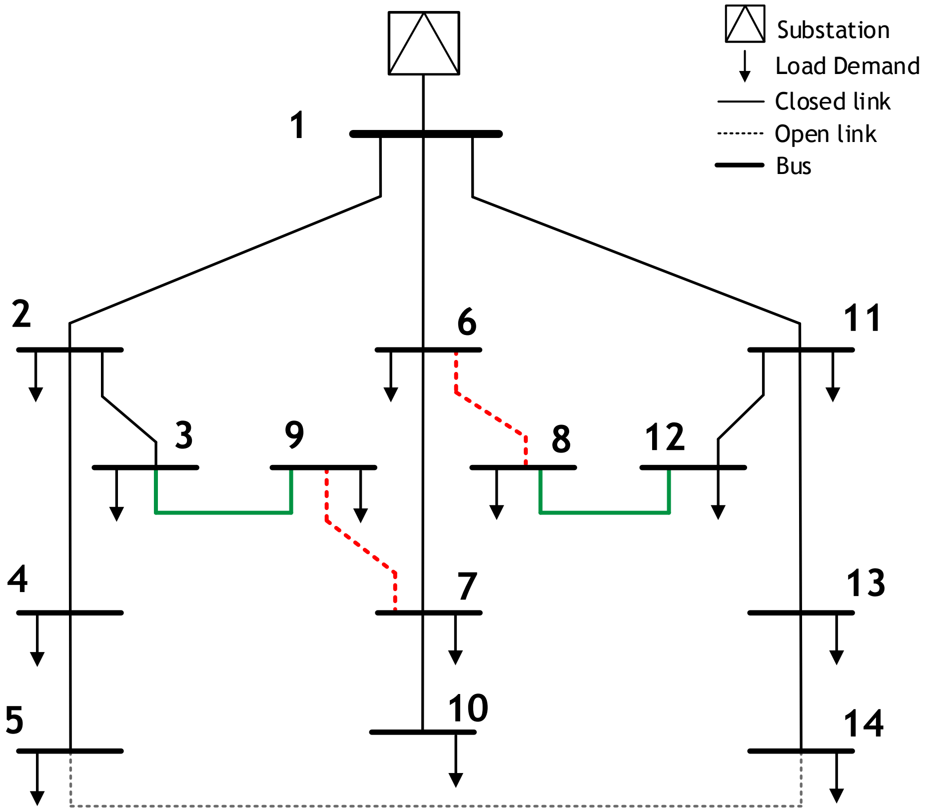


Figure 5.10: Modified 16-Bus DS final configuration.

5.4 Test case: 33-Bus Distribution System

The previous test case presented the working principles of the proposed strategy in a modified 16-Bus DS. An additional larger test case is presented in order to demonstrate the proficiency of the novel coordination strategy in a system that is similar to practical DS.

The system used in this test case is a well known benchmark system, the 12,66 kV 33-Bus DS as it is portrayed in Figure 5.11. The data concerning technical considerations such as line parameters were taken from [76]. For this system, in order to demonstrate the benefits of the proposed strategy, it was assumed for this system that 70% of the total number of users are responsive, and 30% of users are not responsive. This can be seen in terms of the DSO as flexible system load (responsive users) and inflexible system load (non-responsive users). The data regarding the total number of clients is summarized in Table 5.3.

In this system, with a typical price signal the results of the optimization done by the SH in the 33-Bus DS are depicted in Figure 5.12. A similar behavior to the modified 16-Bus test case is noticeable. Regarding the flexible load part of the system, which consists of controllable appliances, EV and ESS systems, a concentration of these resources in the low price periods 11 PM and 3 AM is observed. Evidently, these night load peaks are created due to the time of departure set point to ensure that EVs are fully charged before this time. Regarding the period of 12 AM to 2 AM, the SHs did not allocate loads on this period since it would not be profitable considering only the market electricity price signal.

Therefore, the proposed strategy will generate a DSO price signal in order to prevent these peaks created from the optimization procedures of the SH, only considering the market retail price.

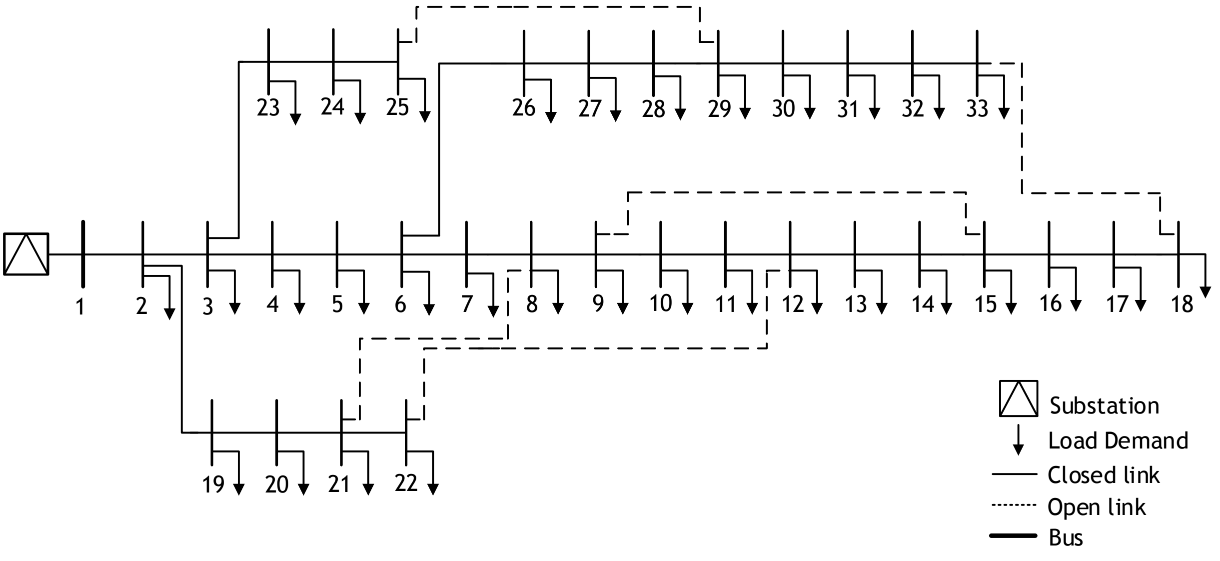


Figure 5.11: The 33-Bus Distribution System.

Table 5.3: Number of clients at each node in the 33-Bus DS.

Node	Number of clients	Non-responsive clients	Number of smart households
1	----	----	----
2	67	20	47
3	60	18	42
4	80	24	56
5	40	12	28
6	40	12	28
7	135	40	95
8	135	40	95
9	40	12	28
10	40	12	28
11	30	9	21
12	40	12	28
13	40	12	28
14	80	24	56
15	40	12	28
16	40	12	28
17	40	12	28
18	60	18	42
19	60	18	42
20	60	18	42
21	60	18	42
22	60	18	42
23	60	18	42
24	280	84	196
25	280	84	196
26	40	12	28
27	40	12	28
28	40	12	28
29	80	24	56
30	135	40	95
31	100	19	81
32	140	42	98
33	40	12	28

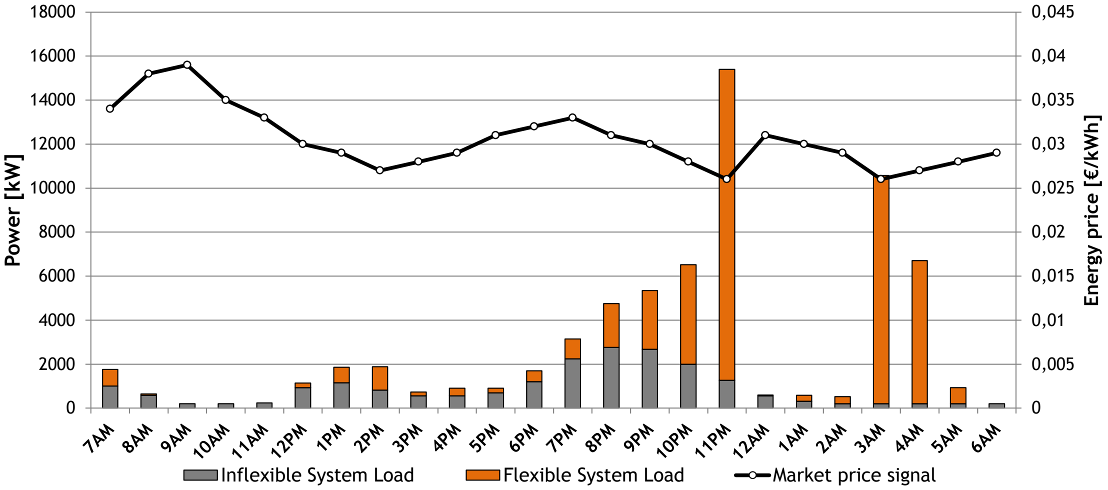


Figure 5.12: Power request from the DS due to the SH optimization.

In Figure 5.13 the generated prices from the DSO with respect to the market retail price are depicted. For the sake of simplicity, regarding the DSO prices generated, the most relevant metrics are observable. During the low price signal from the market retailer, an increase of the price provided by the DSO is noted. Regarding the peak that was existent at 11 PM, the market price signal is at 2,6 cents. Considering this period, the maximum provided price by the DSO reached 1,5 cents. This maximum price was provided to the nodes that contribute most to the energy losses in the system (nodes 24 and 25). These nodes in question receive a higher signal, since they have the highest amount of load allocated to that period and present better chances of shifting some amount of this load to less loaded period. The node that contribute less to the losses in this period is node 10, receiving the minimum price displayed in Figure 5.13 of 0,2 cents.

Another interesting point to note is that not all the low price signal periods of the market retailer price signal were priced by the DSO. For instance, at 2 PM the DSO did not supply a high price on this period since no significant load was allocated at this period, giving no contribution to the loss increase. This proves that the proposed strategy does not respond directly to low values of the price signal provided by the market retailer, but rather the contribution of the load allocation to the increased loss of the system. The low price generated at this signal could be used by the SH to avoid the high penalties that they receive on the loaded periods (11 PM and 3 AM).

After receiving the DSO price signal, the SH re-optimize their consumptions based on two prices. Based on the reported load schedule after this optimization, the new DS network load profile is depicted in Figure 5.14. The first important aspect to be observed is the significant reduction of the network peak at 11 PM. Before the proposed strategy (Figure 5.12) this peak had a magnitude of over 14 MW, which constitutes a considerable stress to the DS with significant contribution to the system losses. However, by adopting the proposed strategy, the load demand at this period was reduced to the values of approximately 3 MW, which represents a reduction of 80%. Moreover, the second network peak that existed at 3 AM was also reduced.

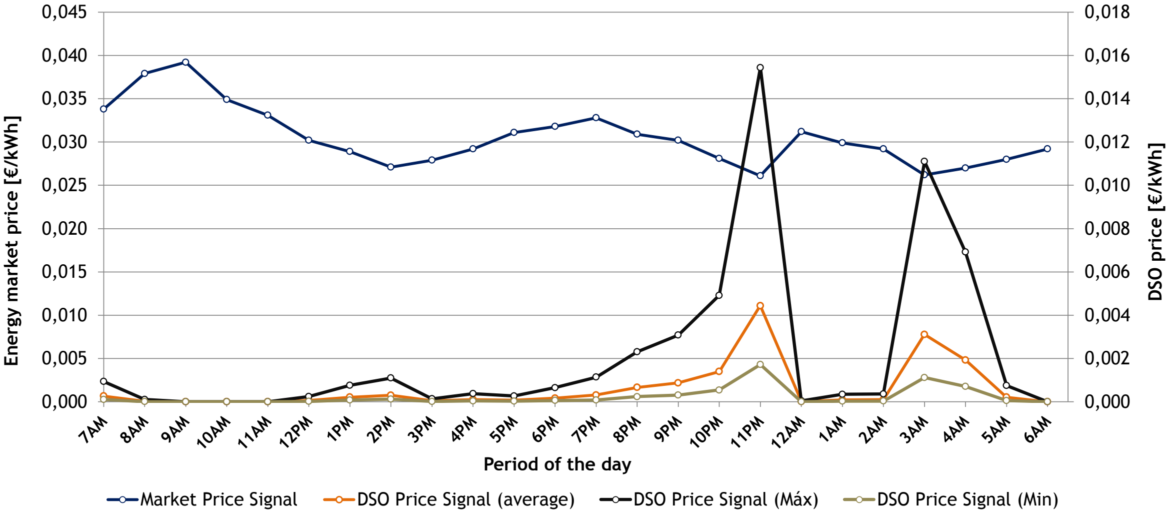


Figure 5.13: Price signal comparison in the 33-Bus DS.

Previously, regarding the period of 3 AM the total power demand was around 10,5 MW. Adopting the new strategy reduced the magnitude of power request reaching the levels of 2,5 MW, which represents a reduction of 76% in this period.

Evidently, the power demand that was previously requested at the low price periods was allocated to other periods. For instance, another hour that presented itself profitable to the SH was the period of 2 PM. It was seen before in Figure 5.12 that this period had low level of load allocation. However, with the proposed strategy, new loads were allocated in this period, reaching the magnitudes of approximately 5,6 MW, representing an increase of 67%. Another conclusion that can be drawn by observing Figure 5.12, is that previously it was not profitable to allocate loads at 5 AM. With the proposed strategy, it is noted that a significant increase on load demand happened on this period (Figure 5.14).

The proposed strategy managed to reduce the impact of high demand peaks during low price periods by the market retailer. This behavior is illustrated in Figure 5.15. It is observable that with the proposed strategy, the demand load curve suffered a significant reduction. Although the new strategy created three additional peaks that were not present before, this magnitude is significantly less when compared to the situation before the proposed strategy.

An important point that the strategy needs to prevent is the overpricing of the users due to the supplied DSO price. This new price signal cannot demotivate the users in abandoning the demand response program. If the SH use the combined prices (Market and DSO price) in the optimization and do not profit from the coordination strategy, the demand response is not achieved and the loss minimization of the DS is not guaranteed.

Therefore, an important point to be taken into account is the total SH cost before and after the proposed strategy. If the costs for the SH after the proposed strategy increase, the strategy compromises the optimization of the SH, resulting in abandoning of the responsive programs.

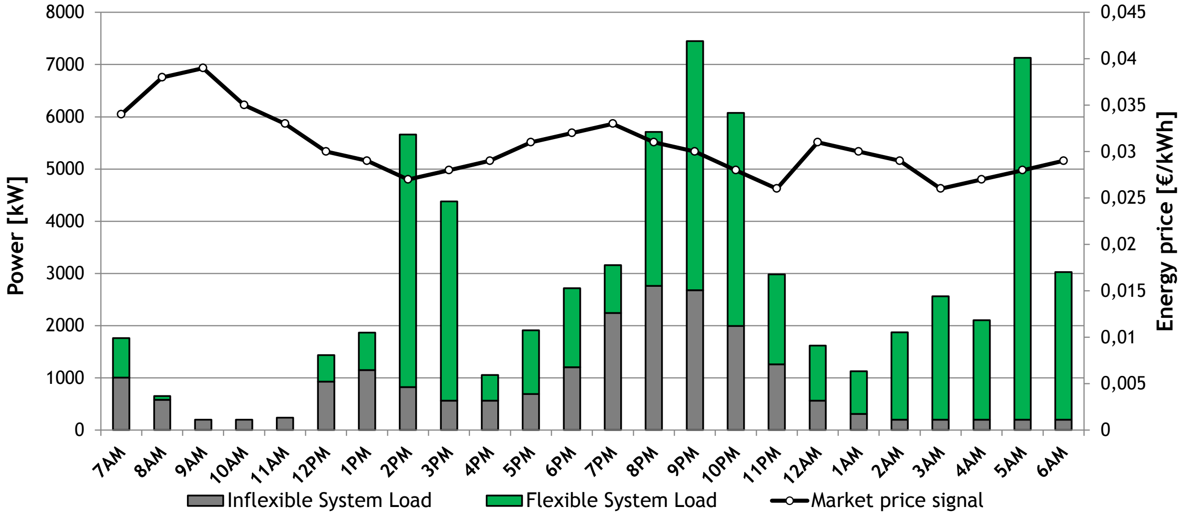


Figure 5.14: Power request from the DS due to the SH optimization after receiving the DSO price signal.

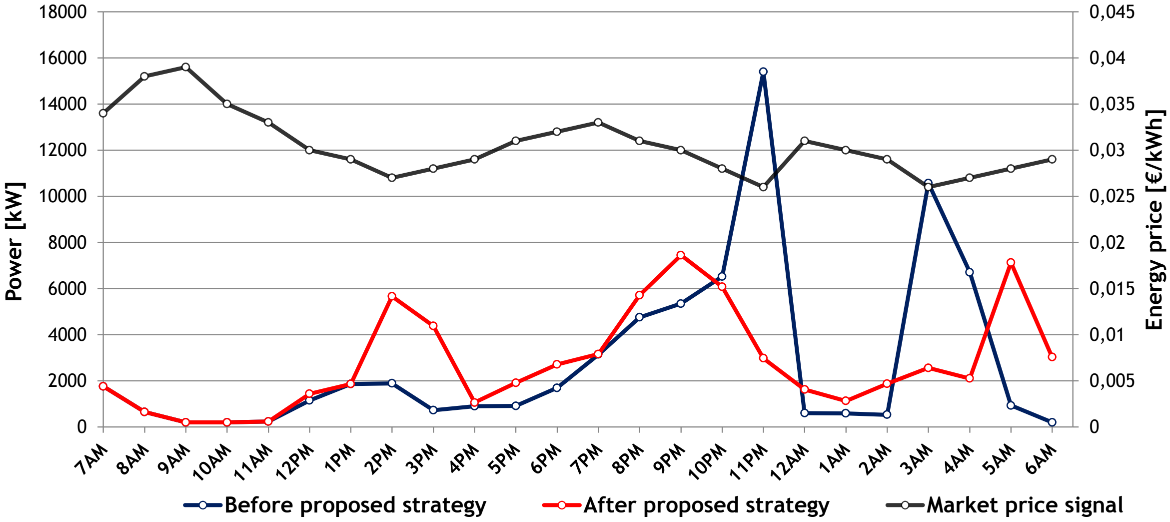


Figure 5.15: Total power request of the SH from grid in the 33-Bus DS.

In Figure 5.16 the aggregated SH cost analysis per node, before and after the proposed strategy is presented. Recall that these costs presented here are not the total costs of the month but rather the costs per day. It is verified that with the proposed strategy there is a reduction of these costs. It is noticeable that nodes with high flexible demand can significantly profit from this strategy.

For instance, regarding nodes 24 and 25, the reduction is visible not only in absolute values such as maximum and minimum cost but also in the average payment. Before the proposed strategy the average payment of node 24 was 0,75 €, but with the proposed strategy this average was reduced to the amount of 0,57 €. Moreover, the maximum payment by a SH at that node before the proposed strategy was 1,1 € and after the proposed strategy was 0,94 €. Evidently, nodes with lesser flexible loads have smaller profits from the proposed strategy, since their contribution to the system losses is smaller when compared to high demand nodes.

It can be concluded that the generated DSO signal does not overprice the users. Additionally, the tariff establishes a fairness for nodes that have low contribution for the losses, in this case, the begging nodes of the distribution radial tree. For instance, this strategy prevents that these nodes that contribute less to the losses pay the same price compared to nodes that most contribute. Observing the SH cost comparison, the DSO signal can be seen as an incentive that helps the SH reduce their billing costs.

The optimal configuration found that minimizes the active system losses is depicted in Figure 5.17. Comparing the default configuration, it led to the opening of branches that connect nodes: 7-8, 9-10, 14-15, 25-29, 32-33. A more detailed analysis of the voltage and the system losses is presented in the next section (5.4.1).

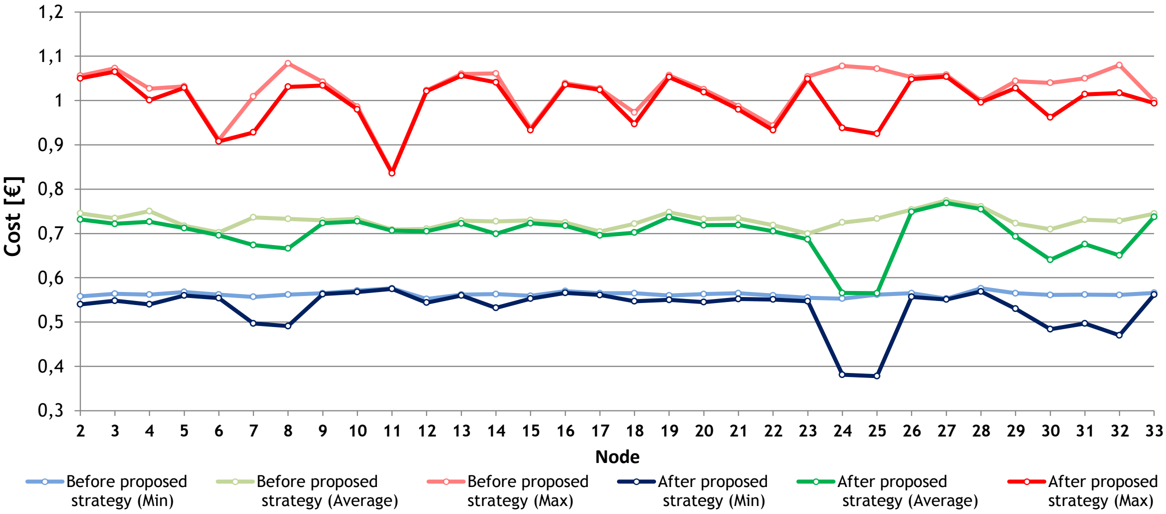


Figure 5.16: Aggregated Smart-Households cost comparison per node in the 33-Bus DS.

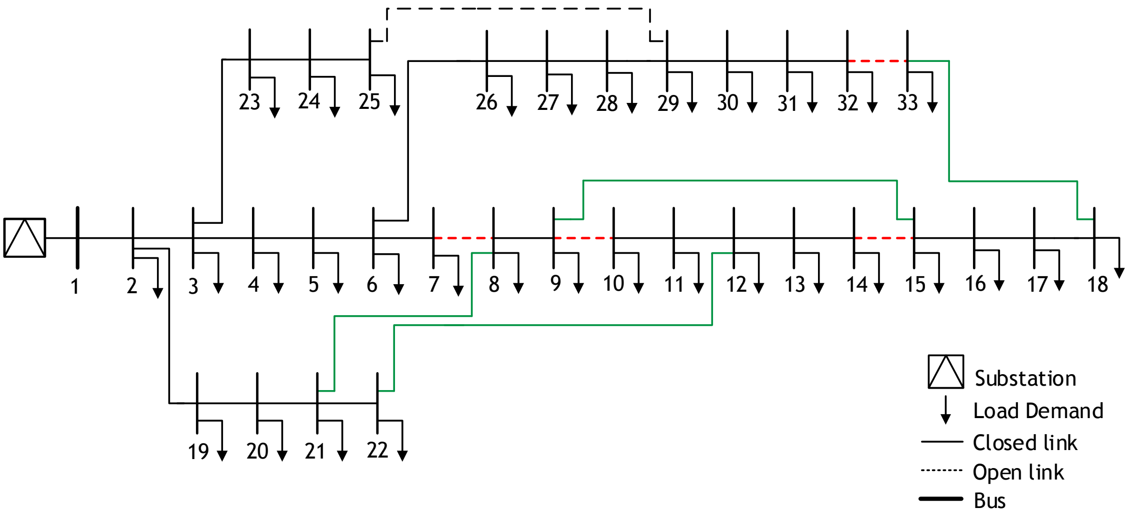


Figure 5.17: Schematic of the 33-Bus DS final topology.

5.4.1 Voltage Analysis and System Losses

It is important to study the impact of the proposed strategy on the DS voltage levels. Therefore, two situations are studied: a peak-clipping instance (11 PM) and an increased peak instance (2 PM). This analysis was done considering the optimal topology presented before. Moreover, the line shunt susceptance ($b_{i,j}^{sh}$) is neglected since the value is relatively small. Therefore, in Figure 5.18 the voltage profile of DS at 11 PM is presented.

Before the proposed strategy, this period had significant load allocation that created an extreme peak to the network. This load demand at this low price hour compromised the voltage profile of the system. Regarding the figure, only three nodes had voltage levels within the acceptable limits ($V \geq 0,95\,pu$). Technically, the deviation of the voltage levels can vary between countries. Considering a $\pm 5\%$ voltage tolerance, the same tolerance limits that are adopted in Portugal, this system presents serious problems.

Regarding this case, there are three nodes that are beginning to display critical signs (depicted as yellow) and extremely critical nodes (depicted as red). It is evident the critical network status under these conditions. The minimum voltage is $0,694\ pu$ belonging to node 33 which is an end node of the radial tree and the average voltage of the system under these operation conditions is at $0,824\ pu$.

Recalling Figure 5.15 on the total power request of the SH from the DS, after the proposed strategy a load demand reduction occurred in this period (11 PM). The reduction of the magnitude of this peak led to a significant improvement of this system (Figure 5.18 b). No nodes are in critical levels, only five nodes that have signs of voltage drops. The rest of the system is above the desired level of $0,95\ pu$. The system at this period is much more stable, being the lowest voltage level at node 33 of $0,938\ pu$ and the average of the system of $0,97\ pu$.

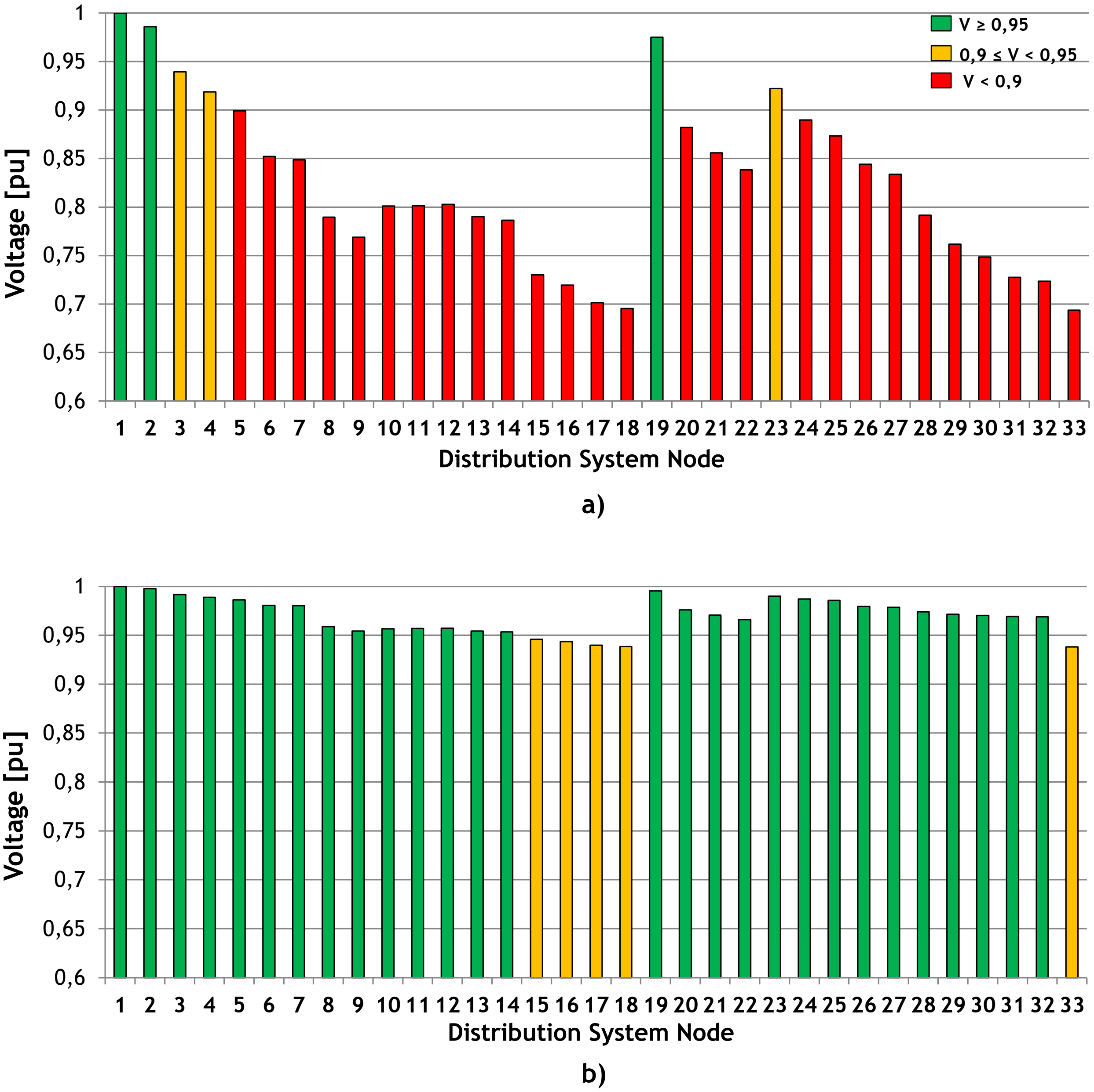


Figure 5.18: Voltage profile in the 33-Bus DS at 11 PM: a) Before the proposed strategy; b) After the proposed strategy.

The improvement of the voltage profile with the reduction of a significant load demand peak is evident. However, a voltage profile needs to be studied regarding an increase of load demand due to the proposed strategy. This situation is referring to the period of 2 PM and is illustrated in Figure 5.19.

Previously at this period low amounts of load were allocated. Regarding this period, the voltage profile of every node in the system is above the desired levels ($V \geq 0,95\ pu$). One can note that overloading at this period will worsen the voltage profile. With the proposed strategy at this period, the deterioration of the voltage levels is noticeable. The two most evident are the critical nodes that were not present before. These are end nodes of the radial tree which get more affected by the allocation of load at this period (node 18: $0,899\ pu$, node 33: $0,898\ pu$). Several nodes were affected with this strategy. Only thirteen nodes managed to maintain the voltage levels within the acceptable limits.

One could be tempted to conclude that the proposed strategy is not worth it in terms of voltage improvements. However, if analyzing the minimum and the average it is noted that improvements are possible with the proposed strategy. Regarding the period represented in Figure 5.19, before the proposed strategy, the stability of the system with a minimum value of $0,9713\ pu$ and an average of $0,9828\ pu$ is evident. It is evident that the allocation of load to this period had an impact in the minimum and average value. After the strategy the system lowest voltage level was at $0,8986\ pu$ and an average of $0,9423\ pu$.

On the other hand, comparing these results to the previous case depicted in Figure 5.18, the benefits from improving the voltage at 11 PM outweighs the consequences of the voltage deterioration at 2 PM.

Evidently, the proposed strategy contributed to the improvement not only in the loss savings but also in the voltage profile. Before the proposed strategy the peak-to-average ratio was at $5,48$. With the proposed strategy a reduction of the metric occurred, leading to a value of $2,67$.

The use of the proposed strategy has several advantages for the DS operation stability. Regarding this comparison the most relevant points are presented in Table 5.4. Note that the losses presented here consider the reactive flow in the network and different voltage levels that differ from the approximation. Comparing the system operation before the proposed strategy the losses represented $8,82\%$ of the total energy supplied. With the proposed strategy this value was reduced significantly, reaching a value of $4,45\%$. Note that this reduction is due to the mitigation of two significant load demand peaks that were mainly responsible for the system losses. In economical terms, the daily cost of losses reduced from approximately 160 € to 86 €. Considering an horizon of a year these costs could be: before the proposed strategy (58400 €) and after the proposed strategy (31390 €). This could represent significant yearly money savings of the order of 27010 €. Evidently this cost can vary according to the applicable market retailer price signal.

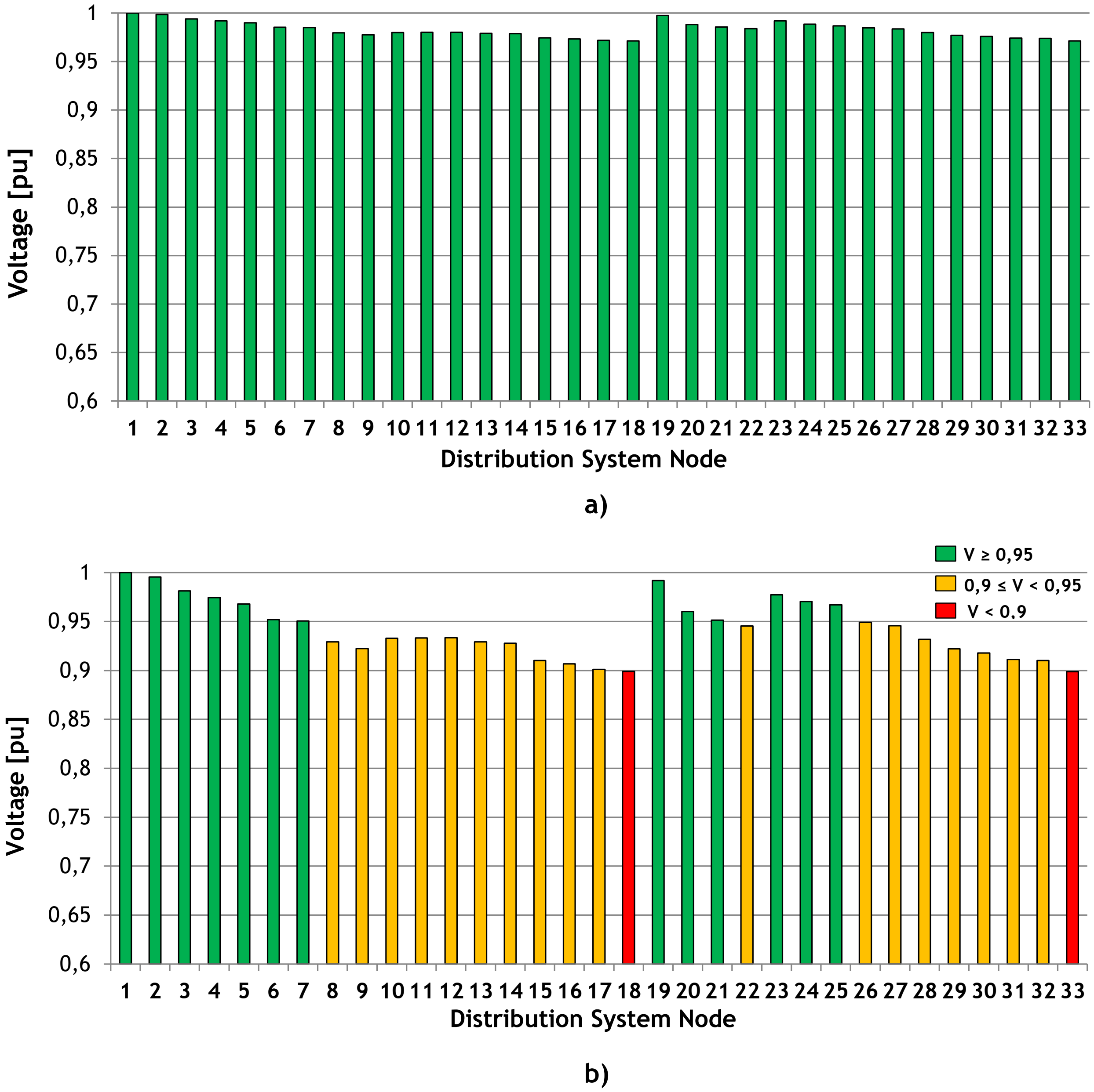


Figure 5.19: Voltage profile in the 33-Bus DS at 2 PM: a) Before the proposed strategy; b) After the proposed strategy.

Table 5.4: Comparison of the 33-Bus DS status before and after the proposed strategy.

	Before proposed strategy	**After proposed strategy**
Active Power Losses [kWh]	5 950,63	2 976,01
Daily Cost of Losses [€]	159,97	86,3
Percentage of DS Losses with respect to the energy supplied	8,82%	4,45%
Peak-to-Average Ratio	5,48	2,67

5.4.2 Extreme-Day price signal

The previous results depicted the network status under a typical market retail price signal. This section, illustrates the behavior of the proposed strategy under an extreme-day price signal. Typically, these are very few days in a year but the proposed strategy needs to be analyzed under these conditions.

In Figure 5.20 the behavior of the network status before and after the proposed strategy is presented. It is expected that the SH allocate their loads to the lowest price period from the provided signal. Evidently, this creates a significant demand peak that needs to be reduced in order to minimize the system losses. With the proposed strategy, the DS nodes will receive a DSO price signal that is higher on these periods in order to demotivate the SH into shifting some of their loads.

However, this simulation represents a scenario where adopting the new proposed strategy is not effective. With the introduction of the new price signal some loads were shifted but a more critical peak was created. This peak was not present previously and the provided price signal motivated the users to allocate their load to this period. Another critical concern is the magnitude of this peak. Before the coordination strategy, the peak reached its maximum value of approximately 14 MW. The proposed strategy led to the creation of a new peak with a bigger magnitude of the order of approximately 16 MW.

In this case the strategy worsen the behavior of the network. It can be easily verified that previously the peak-to-average ratio rated $4,86$ and with the proposed strategy $5,69$. Evidently, this new strategy needs to be augmented in order to respond to these extreme price signals in order to prevent this behavior.

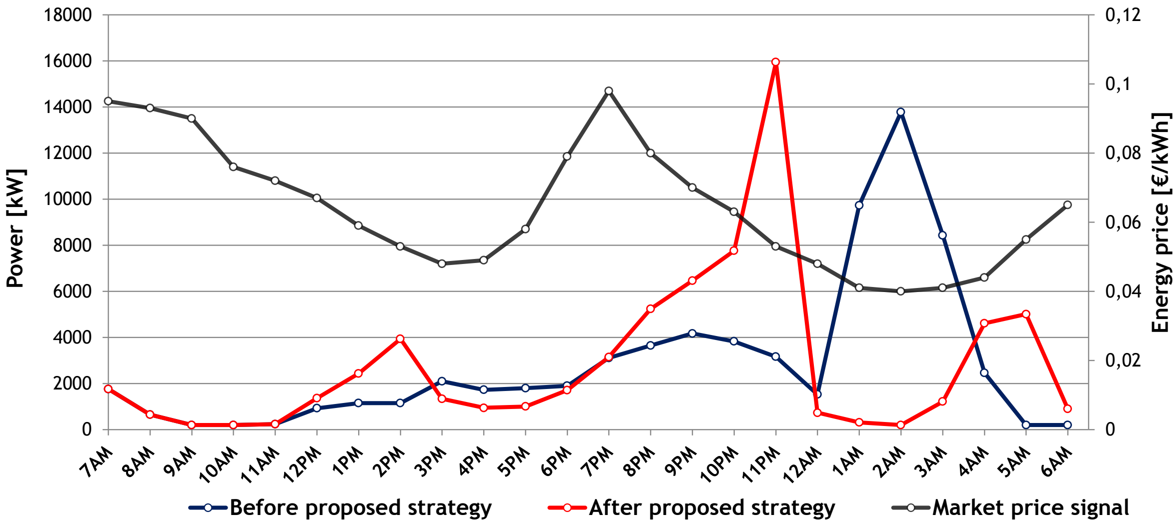


Figure 5.20: Total power request of the SH from the grid in the 33-Bus DS under extreme-day electricity price signal.

In order to demonstrate the importance of the use of advanced computational methods, Table 5.5 presents the most relevant information regarding this subject. These computation times only concern the optimization of the SH, since its the step of the optimization that presents higher computational burden. The simulations were performed under a workstation with two 16 Core Intel CPU clocking at 3,10 GHz and 200 GB of RAM. Additionally, the optimization problems were solved using commercial solver CPLEX 12. It is evident that the use of the adopted technique in handling these problems proves itself worthy for practical deployment.

Table 5.5: Comparison of the computational times.

Test Case	Default Solving Time	Grid Solving Time
16 - Bus System	52 min	1 min 30 s
33 - Bus System	31 min	54 s

Chapter 6

Final Considerations

"To make an end is to make a beginning.
The end is where we start from."

T. S. ELIOT

The distribution systems require optimization regarding their operating condition, in order to minimize the active power losses. The increasing pressure of the efficiency goals, requires the adoption of optimization methods to improve the electrical system. Moreover, the increasing number of automated systems available to the consumers and the introduction of dynamic price signals can be seen as a benefit or a setback regarding the DS operation conditions. A typical SH optimization process was depicted, highlighting the main impacts that it could present to the distribution system. The proposed strategy brings the DSO input closer to the decision taken by the SH. The strategy supplied an additional price signal, that prices the DS nodes according to their contribution to the system losses.

Two test cases were presented in order to demonstrate the benefits of the proposed strategy. On the modified 16-Bus DS test case, the general working principle of the proposed coordination strategy was presented. In this test case the losses were calculated using the approximate form presented on the formulation chapter and the optimal topology was found. This approximation neglects the use of reactive power and considers the voltage to be constant throughout the system. However, the approximation that considers constant voltage is not valid regarding practical considerations, since the concentrated allocation of loads affects the voltage stability of the system.

The behavior of the voltage profile was analyzed in the 33-Bus DS test case. In this test case, it was considered that this system had a bigger percentage of responsive users. The high number of demand responsive users significantly affects the DS performance when the users base only their optimization on the market retail price signal. In this test case, the benefits of the proposed strategy were evident. Not only successfully reduced critical network peaks, but also improved significantly the voltage profiles at critical nodes. However, with the coordination strategy at some periods some nodes worsen their voltage profile due to the new demand allocated at these periods that was not present before. Still, the benefits from reducing the critical peaks from the network, outweighs the consequences of overloading in other periods.

Another significant benefit, apart from the active power loss reduction, is the economic benefit emerging because of reducing of these losses. It was demonstrated that, adopting this new strategy could significantly reduce yearly costs for the DSO, that could provide them a motivation factor to adopt reconfiguration strategies.

It is critical that new pricing strategies do not demotivate the users on adopting demand response programs. Nevertheless, with the proposed strategy the electrical bill paid by the SH can be reduced in several instances. Regarding the strategy, the nodes that profit most from the DSO price signal were the nodes that had bigger loads, since their contribution was larger to the system losses. In the presented test cases, the SH profit from adopting the strategy proven itself useful in further motivating the users into adopting these programs. Additionally, the proposed strategy needs to be improved regarding the extreme-day price signals, since it could deteriorate the network condition.

Another important point that can aid in the decision making process taken by the DSO is the advanced computational methods. With the use of these methods, the DSO can analyze the impacts of the supplied price signal before its broadcast to the SH. Moreover, this technique favors the scalability, thus being suitable for simulating in real distribution systems.

6.1 Future Work

During the development of this work several points were considered interesting to be investigated in the future. Firstly, the coordination strategy needs to be improved in order to address the extreme days electricity price signal. Moreover, the strategy is based only on developing a price based on the node contribution to the losses. An additional future work possibility is the ability of the DSO to provide in the same price signal, not only the penalty from the losses contribution but also an incentive in convenient periods selected by the DSO.

In the future it is important to use the power flow not only as a tool to asses the network status but also during the coordination procedure. Using the power flow study during the reconfiguration of the proposed strategy could lead to improvements while maintaining the voltage limits.

Finally, the application of the proposed approach in a real distribution system would be interesting in order to investigate its practical applicability.

6.2 Research Contributions Resulting from this Work

N.G. Paterakis, **M.F. Medeiros**, J.P.S. Catalão, O. Erdinc, *"Distribution system operation enhancement through household consumption coordination in a dynamic pricing environment"*, in: Proceedings of the **IEEE** Power Tech 2015 Conference, Eindhoven, Netherlands, 29 June - 2 July, 2015 (accepted). Best Student Paper (Basil Papadias Award) Nominee.

N.G. Paterakis, **M.F. Medeiros**, J.P.S. Catalão, A. Siaraka, A.G. Bakirtzis, O. Erdinc, "Optimal daily operation of a smart-household under dynamic pricing considering thermostatically and non-thermostatically controllable appliances", in: Proceedings of the 5th International Conference on Power Engineering, Energy and Electrical Drives — PowerEng 2015 (technically co-sponsored by **IEEE**), Riga, Latvia, May 11-13, 2015.

Bibliography

[1] European Parliament and of the Council. (2009) Directive 2009/28/EC. [Online]. Available: http://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:32009L0028

[2] European Parliament and Council. (2009) Directive 2009/72/EC. [Online]. Available: http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2009:211:0055:0093:EN:PDF

[3] Renewable Energy progress report. (2013) European commission. [Online]. Available: http://ec.europa.eu/energy/renewables/reports/reports_en.htm

[4] T. W. B. Group. (2015) World bank open data. [Online]. Available: http://data.worldbank.org/

[5] K. Qian, C. Zhou, and Y. Yuan, "Impacts of high penetration level of fully electric vehicles charging loads on the thermal ageing of power transformers," *International Journal of Electrical Power & Energy Systems*, vol. 65, pp. 102 - 112, 2015.

[6] J. P. S. Paiva, *Redes de Energia Eléctrica: uma análise sistémica*, 3rd ed. IST Press, 2011.

[7] T. A. Short, *Electric Power Distribution Handbook*, 2nd ed. CRC press, 2014.

[8] T. Gönen, *Electric Power Distribution Engineering*, 2nd ed. CRC Press, 2014.

[9] C. Dortolina and R. Nadira, "The loss that is unknown is no loss at all: a top-down/bottom-up approach for estimating distribution losses," *IEEE Transactions on Power Systems*, vol. 20, no. 2, pp. 1119-1125, May 2005.

[10] S. Kalambe and G. Agnihotri, "Loss minimization techniques used in distribution network: bibliographical survey," *Renewable and Sustainable Energy Reviews*, vol. 29, pp. 184 - 200, 2014.

[11] M. Aman, G. Jasmon, A. Bakar, H. Mokhlis, and M. Karimi, "Optimum shunt capacitor placement in distribution system—a review and comparative study," *Renewable and Sustainable Energy Reviews*, vol. 30, pp. 429 - 439, 2014.

[12] P. Paliwal, N. Patidar, and R. Nema, "Planning of grid integrated distributed generators: A review of technology, objectives and techniques," *Renewable and Sustainable Energy Reviews*, vol. 40, pp. 557 - 570, 2014.

[13] C. Mozina, "Impact of smart grids and green power generation on distribution systems," *IEEE Transactions on Industry Applications*, vol. 49, no. 3, pp. 1079-1090, May 2013.

[14] P. S. Georgilakis and N. D. Hatziargyriou, "A review of power distribution planning in the modern power systems era: Models, methods and future research," *Electric Power Systems Research*, vol. 121, pp. 89 - 100, 2015.

[15] T. Thakur and T. Jaswanti, "Study and characterization of power distribution network reconfiguration," in *Transmission Distribution Conference and Exposition: Latin America, 2006. TDC '06. IEEE/PES*, Aug 2006, pp. 1-6.

[16] L. Tang, F. Yang, and J. Ma, "A survey on distribution system feeder reconfiguration: Objectives and solutions," in *Innovative Smart Grid Technologies - Asia (ISGT Asia), 2014 IEEE*, May 2014, pp. 62-67.

[17] G. Chicco, J. Catalão, A. Bonis, A. Bakirtzis, E. Bakirtzis, V. Cocina, and et al., "Report on the definition of the data structures, component models and mathematical formulation of the developed power flow and fault analysis tool." FP7-Singular, Singular Technical Report, May 2014.

[18] S. Henderson and B. Nelson, *Handbooks in Operations Research and Management Science: Simulation*, ser. Handbooks in Operations Research and Management Science. Elsevier Science, 2006.

[19] M. Lavorato, J. Franco, M. Rider, and R. Romero, "Imposing radiality constraints in distribution system optimization problems," *IEEE Transactions on Power Systems*, vol. 27, no. 1, pp. 172-180, Feb 2012.

[20] 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, Fourth 2012.

[21] J. Bhatt, V. Shah, and O. Jani, "An instrumentation engineer's review on smart grid: Critical applications and parameters," *Renewable and Sustainable Energy Reviews*, vol. 40, pp. 1217 - 1239, 2014.

[22] V. Gungor, D. Sahin, T. Kocak, S. Ergut, C. Buccella, C. Cecati, and G. Hancke, "Smart grid technologies: Communication technologies and standards," *IEEE Transactions on Industrial Informatics*, vol. 7, no. 4, pp. 529-539, 2011.

[23] Z. Fan, P. Kulkarni, S. Gormus, C. Efthymiou, G. Kalogridis, M. Sooriyabandara, Z. Zhu, S. Lambotharan, and W. H. Chin, "Smart grid communications: Overview of research challenges, solutions, and standardization activities," *IEEE Communications Surveys Tutorials*, vol. 15, no. 1, pp. 21-38, 2013.

[24] D. S. Markovic, D. Zivkovic, I. Branovic, R. Popovic, and D. Cvetkovic, "Smart power grid and cloud computing," *Renewable and Sustainable Energy Reviews*, vol. 24, pp. 566 - 577, 2013.

[25] J. Vardakas, N. Zorba, and C. Verikoukis, "A survey on demand response programs in smart grids: Pricing methods and optimization algorithms," *IEEE Communications Surveys Tutorials*, vol. 17, no. 1, pp. 152-178, Firstquarter 2015.

[26] Q. QDR, "Benefits of demand response in electricity markets and recommendations for achieving them," *U.S Department of Energy*, 2006.

[27] C. River, "Primer on demand-side management with an emphasis on price-responsive programs. prepared for the world bank by charles river associates," Tech. Rep, Tech. Rep., 2005.

[28] L. Gelazanskas and K. A. Gamage, "Demand side management in smart grid: A review and proposals for future direction," *Sustainable Cities and Society*, vol. 11, pp. 22 - 30, 2014.

[29] A. J. Wood and B. F. Wollenberg, *Power generation, operation, and control*, 3rd ed. John Wiley & Sons, 2014.

[30] G. Strbac, "Demand side management: Benefits and challenges," *Energy Policy*, vol. 36, no. 12, pp. 4419 - 4426, 2008.

[31] N. O'Connell, P. Pinson, H. Madsen, and M. O'Malley, "Benefits and challenges of electrical demand response: A critical review," *Renewable and Sustainable Energy Reviews*, vol. 39, pp. 686 - 699, 2014.

[32] S. Chan, K. Tsui, H. Wu, Y. Hou, Y.-C. Wu, and F. Wu, "Load/price forecasting and managing demand response for smart grids: Methodologies and challenges," *IEEE Signal Processing Magazine*, vol. 29, no. 5, pp. 68-85, Sept 2012.

[33] P. Siano, "Demand response and smart grids—a survey," *Renewable and Sustainable Energy Reviews*, vol. 30, pp. 461 - 478, 2014.

[34] M. Albadi and E. El-Saadany, "A summary of demand response in electricity markets," *Electric Power Systems Research*, vol. 78, no. 11, pp. 1989 - 1996, 2008.

[35] P. Mallet, P.-O. Granstrom, P. Hallberg, G. Lorenz, and P. Mandatova, "Power to the people!: European perspectives on the future of electric distribution," *IEEE Power and Energy Magazine*, vol. 12, no. 2, pp. 51-64, March 2014.

[36] G. Strbac and D. Kirschen, *Fundamentals of power system Economics*. John Wiley& Sons, Ltd, 2004.

[37] S. Shao, M. Pipattanasomporn, and S. Rahman, "Development of physical-based demand response-enabled residential load models," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 607-614, May 2013.

[38] M. Pipattanasomporn, M. Kuzlu, S. Rahman, and Y. Teklu, "Load profiles of selected major household appliances and their demand response opportunities," *IEEE Transactions on Smart Grid*, vol. 5, no. 2, pp. 742-750, March 2014.

[39] W. Zhang, J. Lian, C.-Y. Chang, and K. Kalsi, "Aggregated modeling and control of air conditioning loads for demand response," *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 4655-4664, Nov 2013.

[40] S. Tindemans, V. Trovato, and G. Strbac, "Decentralized control of thermostatic loads for flexible demand response," *IEEE Transactions on Control Systems Technology*, 2015.

[41] S. Pourmousavi, S. Patrick, and M. Nehrir, "Real-time demand response through aggregate electric water heaters for load shifting and balancing wind generation," *IEEE Transactions on Smart Grid*, vol. 5, no. 2, pp. 769-778, March 2014.

[42] Z. Guo, Z. Wang, and A. Kashani, "Home appliance load modeling from aggregated smart meter data," *IEEE Transactions on Power Systems*, vol. 30, no. 1, pp. 254-262, Jan 2015.

[43] K. Clement-Nyns, E. Haesen, and J. Driesen, "The impact of charging plug-in hybrid electric vehicles on a residential distribution grid," *IEEE Transactions on Power Systems*, vol. 25, no. 1, pp. 371-380, Feb 2010.

[44] L. Pieltain Fernández, T. Román, R. Cossent, C. Domingo, and P. Frías, "Assessment of the impact of plug-in electric vehicles on distribution networks," *IEEE Transactions on Power Systems*, vol. 26, no. 1, pp. 206-213, Feb 2011.

[45] D. Steen, L. Tuan, O. Carlson, and L. Bertling, "Assessment of electric vehicle charging scenarios based on demographical data," *IEEE Transactions on Smart Grid*, vol. 3, no. 3, pp. 1457-1468, Sept 2012.

[46] J. Van Roy, N. Leemput, F. Geth, R. Salenbien, J. Buscher, and J. Driesen, "Apartment building electricity system impact of operational electric vehicle charging strategies," *IEEE Transactions on Sustainable Energy*, vol. 5, no. 1, pp. 264-272, Jan 2014.

[47] J. de Hoog, T. Alpcan, M. Brazil, D. Thomas, and I. Mareels, "Optimal charging of electric vehicles taking distribution network constraints into account," *IEEE Transactions on Power Systems*, vol. 30, no. 1, pp. 365-375, Jan 2015.

[48] E. Veldman and R. Verzijlbergh, "Distribution grid impacts of smart electric vehicle charging from different perspectives," *IEEE Transactions on Smart Grid*, vol. 6, no. 1, pp. 333-342, Jan 2015.

[49] Y. Ma, T. Houghton, A. Cruden, and D. Infield, "Modeling the benefits of vehicle-to-grid technology to a power system," *IEEE Transactions on Power Systems*, vol. 27, no. 2, pp. 1012-1020, May 2012.

[50] M. Yilmaz and P. Krein, "Review of the impact of vehicle-to-grid technologies on distribution systems and utility interfaces," *IEEE Transactions on Power Electronics*, vol. 28, no. 12, pp. 5673-5689, Dec 2013.

[51] A. Conejo, J. Morales, and L. Baringo, "Real-time demand response model," *IEEE Transactions on Smart Grid*, vol. 1, no. 3, pp. 236-242, Dec 2010.

[52] A.-H. Mohsenian-Rad and A. Leon-Garcia, "Optimal residential load control with price prediction in real-time electricity pricing environments," *IEEE Transactions on Smart Grid*, vol. 1, no. 2, pp. 120-133, Sept 2010.

[53] T. Hubert and S. Grijalva, "Modeling for residential electricity optimization in dynamic pricing environments," *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 2224-2231, Dec 2012.

[54] L. P. Qian, Y. Zhang, J. Huang, and Y. Wu, "Demand response management via real-time electricity price control in smart grids," *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 7, pp. 1268-1280, July 2013.

[55] C. Vivekananthan, Y. Mishra, G. Ledwich, and F. Li, "Demand response for residential appliances via customer reward scheme," *IEEE Transactions on Smart Grid*, vol. 5, no. 2, pp. 809-820, March 2014.

[56] M. Sarker, M. Ortega-Vazquez, and D. Kirschen, "Optimal coordination and scheduling of demand response via monetary incentives," *IEEE Transactions on Smart Grid*, 2014.

[57] Y. Ozturk, D. Senthilkumar, S. Kumar, and G. Lee, "An intelligent home energy management system to improve demand response," *IEEE Transactions on Smart Grid*, vol. 4, no. 2, pp. 694-701, June 2013.

[58] S. Althaher, P. Mancarella, and J. Mutale, "Automated demand response from home energy management system under dynamic pricing and power and comfort constraints," *IEEE Transactions on Smart Grid*, 2015.

[59] Y. M. Ding, S. H. Hong, and X. H. Li, "A demand response energy management scheme for industrial facilities in smart grid," *IEEE Transactions on Industrial Informatics*, vol. 10, no. 4, pp. 2257-2269, Nov 2014.

[60] W. Shi, N. Li, X. Xie, C.-C. Chu, and R. Gadh, "Optimal residential demand response in distribution networks," *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 7, pp. 1441-1450, July 2014.

[61] I. Sharma, K. Bhattacharya, and C. Canizares, "Smart distribution system operations with price-responsive and controllable loads," *IEEE Transactions on Smart Grid*, vol. 6, no. 2, pp. 795-807, March 2015.

[62] M. Juelsgaard, P. Andersen, and R. Wisniewski, "Distribution loss reduction by household consumption coordination in smart grids," *IEEE Transactions on Smart Grid*, vol. 5, no. 4, pp. 2133-2144, July 2014.

[63] N. Paterakis, S. Santos, J. Catalao, O. Erdinc, and A. Bakirtzis, "Coordination of smart-household activities for the efficient operation of intelligent distribution systems," in *Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), 2014 IEEE PES*, Oct 2014, pp. 1-6.

[64] N. Paterakis, O. Erdinc, A. Bakirtzis, and J. P.S. Catalão, "Optimal household appliances scheduling under day-ahead pricing and load-shaping demand response strategies"," *IEEE Transactions on Industrial Informatics*, 2015 (forthcoming).

[65] O. Erdinc, N. Paterakis, T. Mendes, A. Bakirtzis, and J. P.S.Catalao, "Smart household operation considering bi-directional ev and ess utilization by real-time pricing-based dr," *IEEE Transactions on Smart Grid*, vol. 6, no. 3, pp. 1281-1291, May 2015.

[66] N. Paterakis, A. Mazza, S. Santos, O. Erdinc, G. Chicco, A. Bakirtzis, and J. Catalao, "Multi-objective reconfiguration of radial distribution systems using reliability indices," *IEEE Transactions on Power Systems*, no. 99, pp. 1-15, 2015.

[67] H. Ahmadi and J. Marti, "Linear current flow equations with application to distribution systems reconfiguration," *IEEE Transactions on Power Systems*, pp. 1-8, 2014.

[68] G. M. Appa, L. S. Pitsoulis, and H. P. Williams, *Handbook on modelling for discrete optimization*. Springer Science & Business Media, 2006, vol. 88.

[69] E. Romero-Ramos, J. Riquelme-Santos, and J. Reyes, "A simpler and exact mathematical model for the computation of the minimal power losses tree," *Electric Power Systems Research*, vol. 80, no. 5, pp. 562 - 571, 2010.

[70] P. S. Pricing. (2015) A Smart Electricity Rate from Ameren Illinois. [Online]. Available: http://www.powersmartpricing.org/

[71] P. Sotkiewicz and J. Vignolo, "Towards a cost causation-based tariff for distribution networks with dg," *IEEE Transactions on Power Systems*, vol. 22, no. 3, pp. 1051-1060, Aug 2007.

[72] GAMS. (2015) General Algebraic Modeling System. [Online]. Available: http://www.gams.com

[73] A. Tascikaraoglu, A. Boynuegri, and M. Uzunoglu, "A demand side management strategy based on forecasting of residential renewable sources: A smart home system in Turkey," *Energy and Buildings*, vol. 80, pp. 309 - 320, 2014.

[74] K. Geurts, "Modal choice for travel to work and school: recent trends and regional differences in Belgium," Federal Planning Bureau and Federal Public Service Mobility and Transport, Working Paper, Oct 2014.

[75] S. Civanlar, J. Grainger, H. Yin, and S. Lee, "Distribution feeder reconfiguration for loss reduction," *IEEE Transactions on Power Delivery*, vol. 3, no. 3, pp. 1217-1223, Jul 1988.

[76] M. Baran and F. Wu, "Network reconfiguration in distribution systems for loss reduction and load balancing," *IEEE Transactions on Power Delivery*, vol. 4, no. 2, pp. 1401-1407, Apr 1989.