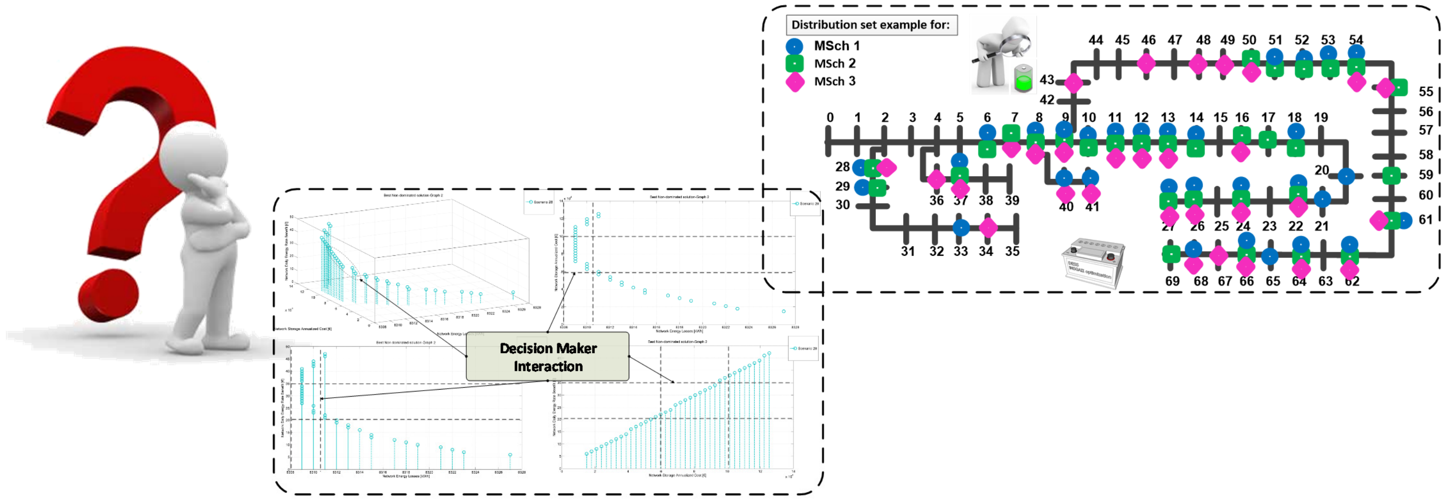

José António Ribeiro Gonçalves

Methodology for real impact assessment of the best location of distributed electric energy storage systems

Doctoral Thesis on Sustainable Energy Systems
supervised by Professor António M. O. Gomes Martins and Professor Luís M. P. Neves
and submitted to the Faculty of Sciences and Technology of the University of Coimbra

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Universidade de Coimbra

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Methodology for real impact assessment of the best location of distributed electric energy storage systems

Submitted to the Faculty of Sciences and Technology of the University of Coimbra in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Sustainable Energy Systems.

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Abstract

This thesis presents a methodology to assist decision makers on the assessment of feasible solutions to integrate a distributed electric energy storage system (DEESS) in an urban environment, as a tool to provide power and energy services to the electric network. Requiring data easily found in the Portuguese energy sector, the developed methodology uses prototype diagrams of electricity demand, electricity prices and renewable electricity generation to optimize the location of electric energy storage units. The profile prototypes are based on real data, obtained through clustering techniques, and an improved genetic algorithm, based on Non-dominated Sorting Genetic Algorithm-II (NSGAII) is used for the optimization that allows the most suitable locations of DEESS units to be found.

The present work considers expected attitudes of the main stakeholders towards DEESS implementation and discusses possible regulatory framework options to define the DEESS business model in order to stimulate the appearance of market players intending to invest on energy storage systems, such as the use of a feed-in-tariff scheme.

The methodology was applied to a case study, using the nanophosphate lithium-ion ($LiFePO_4$) battery technology due to its increasing use in electricity networks and to the advantages it offers when compared to other commercially available technologies. The choice of location uses a definition of the best schedule of operation, while optimizing four objective functions: the minimization of losses, voltage deviations and investment cost, and the maximization of the net gains of exploiting the differences among time-varying energy prices. This last objective included an externality assessment based on the European emissions trading system, trying to account for the main associated benefits of DEESS.

Results showed that the best DEESS location depends on the energy service to be provided, namely of the goal that defines the management scheme of the storage system. This feature suggests the need to incorporate this level of decision on the multiple objective formulation and makes the developed methodology appropriate to be used by different types of stakeholders, such as a private investor, the DSO or a public authority.

Keywords: Improved genetic algorithms, multiobjective assessment, distributed electric energy storage, energy profiles, distribution networks, load leveling energy service.

Resumo

Esta tese apresenta uma metodologia para ajudar os decisores a encontrar soluções viáveis que permitam integrar um sistema de armazenamento de energia elétrica distribuída (DEESS) num ambiente urbano, como uma ferramenta para fornecer serviços de potência e de energia para a rede elétrica. Requerendo dados de fácil obtenção no setor elétrico Português, a metodologia desenvolvida utiliza diagramas protótipo de consumo de energia elétrica, de preços de eletricidade, e de geração renovável de eletricidade, visando otimizar a localização das unidades de armazenamento de energia elétrica. Os diagramas protótipo são baseados em dados reais, sendo obtidos através de técnicas de agrupamento (clustering). Para a otimização é utilizado um algoritmo genético melhorado baseado no Non-dominated Sorting Genetic Algorithm-II (NSGAII) que permite encontrar os locais mais adequados para as unidades do DEESS.

O presente trabalho considera as atitudes expectáveis dos principais interessados na implementação de um DEESS e discute possíveis opções de enquadramento regulatório, tais como o uso de um incentivo nas tarifas, para definir um modelo de negócio que estimule o aparecimento de intervenientes no mercado com vontade de investir em sistemas de armazenamento de energia.

A metodologia foi aplicada a um estudo de caso, utilizando a tecnologia de baterias de Nanofosfato de iões de lítio (LiFePO4) devido a sua crescente utilização em redes de eletricidade e às vantagens oferecidas quando comparado a outras tecnologias disponíveis no mercado. A escolha das localizações usa uma definição do melhor horário de funcionamento enquanto otimiza quatro funções objetivo: a minimização das perdas, desvios de tensão e custo de investimento, e a maximização dos ganhos líquidos de exploração das diferenças entre os preços da energia que variam no tempo. Neste último objetivo é incluída uma avaliação de externalidades com base no sistema europeu de comércio de emissões, a fim de tentar contemplar os principais benefícios associados ao armazenamento.

Os resultados mostraram que a melhor localização de DEESS depende do serviço de energia a ser fornecida, nomeadamente nos objetivos que definem o regime de gestão do sistema de armazenamento. Esta característica sugere a necessidade de incorporar este nível de decisão na formulação multiobjetivo e torna a metodologia desenvolvida apropriada para ser usada por diferentes tipos de interessados, tais como investidores privados, o DSO ou uma autoridade pública.

Palavras chave: Algoritmos genéticos melhorados, avaliação multiobjectivo, armazenamento distribuído de energia elétrica, perfis de energia, redes de distribuição, serviço de suavização de carga

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Glossary of frequently used acronyms

Acronyms	
AMC	Average marginal costs
ANN	Artificial neural network
BESS	Battery energy storage system
C/D	Charge/discharge
CA	Cranking amperes
CNN	Competitive neural networks
CRF	Capital recovery factor
DEESS	Distributed electric energy storage system
DM	Decision maker
DoD	Depth of discharge
DSO	Distribution system operator
EA	Evolutionary algorithms
ESS	Energy storage system
EU ETS	European emissions trading system
EV	Electric vehicles
GA	Genetic algorithms
GHG	Greenhouse gas
HM	Hierarchical clustering method
HV	High voltage
iNSGA-II	improved NSGA-II
LD	Load demand
MIBEL	Iberian electricity market
MSch	Management scheme
NEL	network energy losses
NERB	Network energy rate benefit
NSAC	Network storage annualized cost
NSGA-II	Non-dominated Sorting Genetic Algorithm-II
NVqmd	Network voltage quadratic mean deviation
pc	Probability crossover
PC	Power converter
PL	Power losses
pm	Probability mutation
PSO	Particle swarm optimization
PT	Power transformer
RDS	Radial distribution system
RE	Renewable energy
RES	Renewable energy sources
SOM	Self-organizing maps
SRP	Special regime producer
TSO	Transmission system operator
V2G	Vehicle-to-grid

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1 Introduction

The need to combine distributed generation, continuous load growth, increasing power quality requirements of electronic loads and higher regional power transfers in a (nowadays) largely interconnected network, presents new challenges to power systems.

These new challenges can lead to a complex and less secure power system operation, especially because power plants may not be able to follow new demands, as a result of technical, economic, environmental, and/or governmental regulation constraints (Ribeiro et al., 2001),(R.M. Vitorino et al., 2013).

In the context of smart grids and micro grids, distributed electric energy storage systems (DEESS) are presented as an option to enable the optimal use of resources, by providing the capability of effectively balancing supply and demand (EPRI, 2010). However, a methodology is needed to evaluate the impact of storage, as well as the best locations for DEESS units, in order to provide specific energy services to the network.

1.1 Motivation and research objectives

This thesis presents a methodology to assist decision makers on the assessment of feasible solutions regarding the integration of a DEESS in an urban environment, as a tool to provide power and energy services to the electric network. The developed methodology uses profile prototypes based on real data, obtained through clustering techniques. These profiles, of electricity demand, electricity prices and renewable electricity production, are used to optimize the placement of electric energy storage units by an improved genetic algorithm based on the Non-dominated Sorting Genetic Algorithm-II (NSGAII). The thesis considers expected attitudes of the main stakeholders towards DEESS implementation and discusses the possible regulatory framework options to define the DEESS business model.

The novelty of the proposed methodology is to combine the determination of the best location for the storage units with the definition of the best schedule of operation when simultaneously minimizing investment costs, energy losses and voltage deviations, as well as maximizing the economic benefit resulting from the energy exchange with the grid.

The proposed methodology aims to provide the decision-maker (DM) with insight on the impacts associated with possible energy storage systems (ESS) management schemes, as well as to propose a pricing scheme within the current legal framework for the ESS exploitation. Considering plausible management schemes based on possible private stakeholders objectives, the assessment of its impacts, both technical and economic, increases their perception of the characteristics of available DEESS options.

The specific goals of the research may be formulated as the following research question:

- In which circumstances can urban DEESS be a feasible solution?, given:
    - Technological costs / Power Generation Costs;
    - Availability / Energy Services provided;
    - Location and sparsity of the storage units.

1.2 Scope and limitations

The developed methodology could be used in any type of network as long as a correct characterization is done. Considering the assessment of technical impacts in its current state, the proposed methodology is suited for energy services assessment.

The operation of ESS is constrained by the individual capacities of each storage unit and additional specifications, namely: the required voltage for the power inverter, the power limit considering the bus constraints in the network to be assessed, and the physical limit of each individual storage solution for a maximum volume of 1m^3, specified in order to be easily installed within a typical distribution transformer station (EDP Distribuiçao, 2004).

1.3 Thesis structure

This doctoral thesis is organized in five chapters, each one describing specific work carried out during the development of the thesis. This chapter presented an introduction, discussing the motivation, objectives and research question to be answered, and the scope and limitations of the developed work.

The remaining chapters are organized as follows:

- Chapter 2 presents a literature review on energy storage operation, possible applications, barriers and some principles for assessing the economic cost and benefits of energy storage systems. This chapter describes different assessment methodologies and common evaluation parameters and techniques used in the literature. A significant part of the text is dedicated to multiobjective optimization and the use of an optimized NSGAII which was regarded as an efficient way to solve the problem given its nature. A final section was dedicated to the evaluation of externalities, namely the evaluation of environmental impacts by valuing CO2 emissions.
- Chapter 3 presents the proposed methodology for assessing energy storage systems. The chapter includes a detailed description of the clustering methods used and the development of prototype diagrams. The second section of the chapter describes a proposal of a pricing scheme for the energy recovered from storage, based on the current legal framework, considering hypothetical assumptions on how energy storage systems could be integrated/treated. Finally, the chosen optimization method is also described, detailing its design and choice of settings.
- Chapter 4 presents the application of the methodology to a case study based on a IEEE standard 69 bus network. The prototype diagrams used are determined through the clustering methods described, with information obtained from the Portuguese energy sector. The chapter also details the characteristics of the chosen technology, network and energy storage system working profiles. Lastly, a detailed analysis of the results is presented.
- Chapter 5 presents the final conclusions, highlighting the potential and limitations of the proposed methodology, and suggesting future work to further developments and improvements.

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2 Literature review

2.1 Energy storage

Continuous load growth, increasing power quality requirements of electronic loads and higher regional power transfers in a largely interconnected network, can lead to complex and less secure power system operation, especially because new economic, environmental, technical, and governmental regulation constraints make it difficult to follow the continuous growth of demand (Ribeiro et al., 2001), (Ipakchi & Albuyeh, 2009).

In the recent past, energy storage for daily periods seemed economically unfeasible (Barton & Infield, 2004). However, the rising cost of oil and the need to rethink the management of the electricity grid (to meet the demands of current loads) led to consider storage, either centralized or decentralized, as an opportunity to help solving problems of capacity and reliability of the network (Divya & Østergaard, 2009; Ribeiro et al., 2001). The SmartGrids European Technology Platform (SmartGrids, 2012) presents storage as a key solution, within five of the six research areas presented in Figure 2-1, in order to achieve the EU 20-20-20 goals, as well as to obtain the envisioned CO_2 reduction of 80% by 2050, despite the high acquisition and maintenance costs. The integration of storage technologies, addressing different needs (e.g. quick response, high grid security, long-term energy storage, lowering peak demand, among others) will help tackling these challenges.

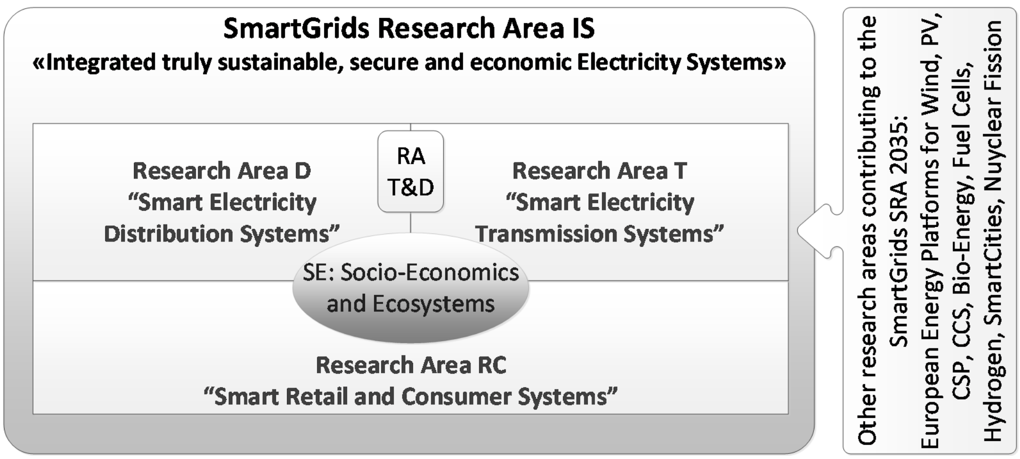


Figure 2-1 – Research areas in Strategic Research Agenda for Europe's electricity networks of the future (SmartGrids, 2012)

Electric grids such as the Danish, with a high wind power and distributed generation penetration, are being envisioned as the model of future electricity networks in many countries. Although about 20% of the total electricity demand of Denmark was met by wind power alone in 2007, there are still ambitious targets to increase the wind power penetration to 50%. In this context, different technologies are being examined, including storage (Divya & Østergaard, 2009). In fact, the integration of renewable sources requires considerable further development of storage systems to contribute for a more sustainable energy use (H. Chen et al., 2009), (Ibrahim et al., 2008). Despite all the associated constraints regarding the current electric energy storage technologies, they have strong potential benefits, such as the ability to stabilize the highly variable load diagram, making it as constant as possible, thus creating a sustainable, efficient, reliable and environmentally friendly alternative to the conventional energy system (H. Chen et al., 2009). Faruqui et al (2007) also highlighted the ability to improve the load factor because a great percentage of the installed capacity is only used during roughly 80 to 100 hours/year, corresponding to 8-12% of load factor. In other words, much of the installed capacity is currently underutilized due to the short periods of operation at full load, because there is no alternative solution.

Even considering the high acquisition and maintenance costs of current technologies, the role of ESS is considered crucial and, therefore, it is very important to capture the maximum added value of energy storage (SmartGrids, 2012).

2.1.1 Electric energy storage operation

By the year 2035 it is expected that a large fraction of the generation capacity in Europe will have irregular and/or highly variable availability. Due to technological improvements, it is expected that ESS in Europe and USA will grow by 10 to 15% (and by larger figures in Japan), in a near future, motivating a major change in the electricity industry (H. Chen et al., 2009). The development of ESS is essential to the achievement of a more flexible and controllable electric network (e.g. smart grids), enabling higher levels of demand side management, increased proximity of generation to the loads, integration of non-dispatchable generation from renewable sources, and other forms of decentralized production (Ipakchi & Albuyeh, 2009), (Beer et al., 2012).

Although ESS are being envisaged as an important part of a smarter grid, their usefulness may apply to the existing grid technologies as long as there is a communication system that links them to the distribution system operator (DSO). Nevertheless, the use of smart grids is crucial to make full use of the capabilities of smaller and larger generation and loads.

Some authors propose the introduction of an aggregator in order to fully realize the benefits of ESS (Battistelli et al., 2012), (Kristoffersen et al., 2011). However the need to develop the power system beyond the closed infrastructure of an aggregator is also defended, to address specific needs, in such a way that all generation and consumption units can participate automatically and individually as ancillary services, without the need for the control by the DSO, transmission system operator (TSO), utility or even an aggregator (SmartGrids, 2012).

Within a smart grid paradigm of network management, some authors defend that the increase of storage capacity, besides solving network problems, may facilitate the adoption of plug-in hybrid vehicles or electric vehicles (EV), mitigating some requests from the network (Sovacool & Hirsh, 2009), (Ipakchi & Albuyeh, 2009).

The use of intelligent charging/discharging (C/D) management schemes could release network capacity, minimizing or deferring supply-side capacity expansion, decreasing network losses and overall electric systems running costs (both in production and delivery costs), avoiding short interruptions and some voltage quality problems, shaving power peaks and smoothing load curves (Lassila et al., 2012), (Almeida et al., 2011),(Lopes et al., 2011),(Martins, 1999), (Sutanto & Lachs, 1998).

Different market operation frameworks within the smart grid concept are also presented as important tools to avoid other new types of problems such as potential shortage of generation capacity or the increased difficulty in optimizing the management of the grid to accommodate new dispersed loads and generators that could significantly influence the mix of generation and consequently, electricity prices and emissions (Hadley & Tsvetkova, 2009), (Rocha Almeida et al., 2010). Within this paradigm the confidence on the impact assessment is influenced by the used grid control architecture as well as by other characteristics such as the network connections and used storage technology (Rocha Almeida et al., 2010).The key characteristics of available technologies of accumulators are their energy densities (up to 150 and 2000Wh/kg for lithium) and technological maturity. Generally the Ragone's diagram is used (Ibrahim et al., 2008) to represent the performance in terms of ratio of mass to energy and power. Although this diagram is useful when the size of the storage systems is important, it is not enough. Even considering the present technology limitations, instantaneous, short-term and mid-term applications seem to be commercially feasible. Although the storage of large amounts of energy would be desirable, even batteries of modest power and able to deliver only during seconds or minutes, seem to be cost-effective when designed for storage periods of less than 5 h (Divya & Østergaard, 2009).

2.1.2 Electric energy storage possible applications and services

The adoption of distributed energy storage allows an optimization of resources by providing the capability of effectively balancing supply and demand (Kintner-Meyer. et al., 2007), (EPRI, 2010), (Ibrahim et al., 2008), (Lopes et al., 2011). The ideal ESS solution in urban environments should have means of rapidly damp oscillations, respond to sudden changes in load, supply load during transmission or distribution interruptions, provide spinning reserve, correct load voltage profiles with rapid reactive power control, and still allow the generators to balance the system load at their normal speed (Sutanto & Lachs, 1998), (Ribeiro et al., 2001), (Lopes et al., 2011), (Almeida et al., 2011).

Nevertheless, according to several sources, (Electricity Storage Association, 2011; Ibrahim et al., 2008; S. M. Schoenung & Hassenzahl, 2003; S. M. Schoenung, 2001), current batteries are mature and with appropriate technologies, able to be used in network applications. For instance, there are 190 sites in Japan with more than 270MW of stored energy suitable for 6 hours of daily peak shaving (Electricity Storage Association, 2011). In Bewag (Germany), 7 MW/14MWh batteries were installed for frequency regulation; and the Chino substation of Southern California Edison, has 10MW/40MWh for load levelling, rapid spinning reserve and instantaneous frequency control (Divya & Østergaard, 2009).

According to Barton and Infield (2004), possible benefits of increased energy storage capacity (spanning a few hours) are both the relief of stress situations of the distribution electric grid and an improved use of reactive power. The first would allow the network to respond to higher demand levels without causing excessive load flow in the transmission network, and the latter responds to voltage disturbances caused by embedded renewable generation.

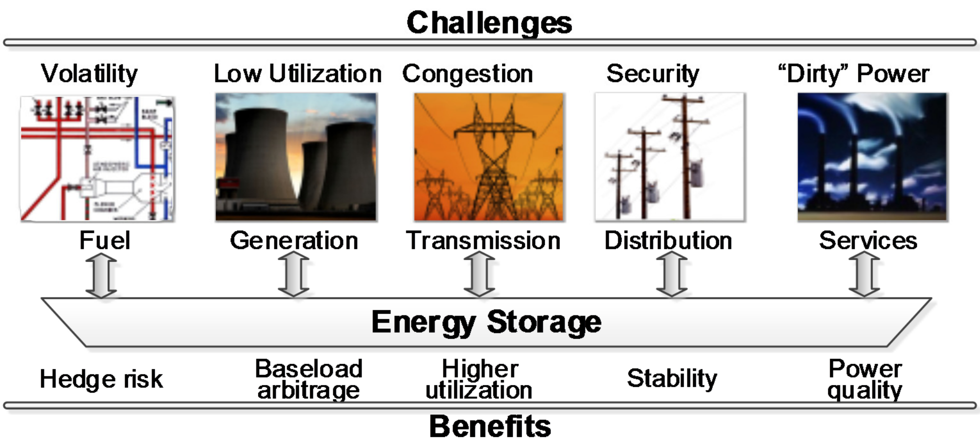


Figure 2-2 – Challenges and Benefits in the electricity chain (H. Chen et al., 2009)

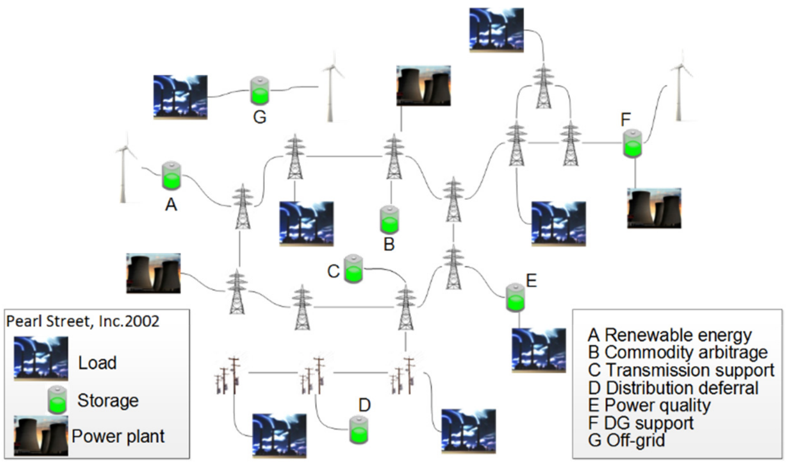


Figure 2-3 – Energy storage applications into grid (H. Chen et al., 2009)

According to H. Chen et al. (2009), Figure 2-2 and Figure 2-3 present the possible applications of ESS. These authors and F. Rahman et al. (2012) claim that electric energy storage technologies provide three primary functions: energy management, bridging power, power quality and reliability. However, there are other definitions for more specific applications. It is important to note that no single storage system based on commercially available technologies currently meets all the requirements for an ideal electric ESS - being mature, having a long lifetime, low cost, high density and high efficiency, and being environmentally benign. Each storage system has a suitable application range. For utility applications, cost is the most important factor and storage facilities need to be sized in tens or hundreds of megawatts with a few hours duration. On the other hand, automotive applications have small footprints and high power outputs (F. Rahman et al., 2012).

According to H. Chen et al. (2009), each service previously presented can be performed as one of the options in Table 2-1.

Table 2-1 - Application Category Specifications (H. Chen et al., 2009)

Service	Power rating	Application
Medium-scale energy management	10 - 100MW	Load leveling, ramping/load following, and spinning reserve;
Bridging power	0.1 -10MW	Assure continuity of service when switching from one source of energy generation to another
Power quality	Lower than 1 MW	Voltage drop, flicker mitigation and short duration uninterruptible power supply (UPS)

We can observe that the capacity range for each application is not well defined in Table 2-1 and Table 2-2, varying among authors. Moreover, energy storage capacity is specifically determined by the time duration required for delivery or discharge. Applications tend to fall into time categories of very short, short, long, and very long duration, as shown in Table 2-3, according to the time category applications recognized by utilities and customers.

Table 2-2 - Application Category Specifications (S. M. Schoenung & Hassenzahl, 2003)

Representative Applications	Discharge Power Range	Discharge Time Range	Stored Energy Range
Load levelling, spinning reserve	10-1000 MW	1-8 hrs	10-8000 MWh
Peak shaving, transmission deferral	100-2000 kW	0.5-4 hrs	50-8000 kWh
End-use power quality and reliability	0.1-2 MW	1-30 sec	0.1-60 MJ (0.028-16.67 kWh)

Considering the Portuguese supply failures presented by the DSO in 2011(EDP Distribuição, 2011), the majority of distribution grid problems were related to short duration problems. Hereupon and given the following Table 2-3 information, we may conclude that electric ESS seems suited for applications of short and very short duration, such as transmission and distribution stabilization or renewable matching.

Table 2-3 – Types of applications as a function of time span duration (S. M. Schoenung, 2001)

Very short duration	Short duration	Long duration	Very long duration
End-use ride through, power quality, motor starting; Transit; T&D stabilization.	Distributed generation (peaking); End-use peak shaving (to avoid demand charges); Spinning reserve – rapid response within 3 sec to avoid automatic shift; Spinning reserve – conventional (respond within 10 min); Telecommunications back-up; Renewable matching (intermittent); Uninterruptible Power Supply;	Generation, load leveling; Ramping, load following.	Emergency back-up; Seasonal storage; Renewables back-up.

Considering the possible exchange of ancillary services between the TSO and DSO, the existence of a storage system in the distribution grid might be a solution to perform ancillary services in a more cost-effective way (SmartGrids, 2012). Different technologies may be used for different applications, according to the discharge time: technologies with a long discharge time will be used to secure the capacity of renewable energy sources (RES), while those with a short discharge time will be adopted to perform frequency regulation or voltage control.

As small distributed generation systems are expected to spread in urban environments with their almost random, uncontrolled nature, the assessment of the value of small scale storage against supply interruptions will be very important (SmartGrids, 2012). In order to understand the technical and economic viability of each type of system, it is important to assess all the associated costs and benefits, and verify whether there is overall economic justification (SmartGrids, 2012), (Hittinger et al., 2012). This will certainly lead to further research development related to the distribution network management.

The energy service to be provided determines the technology to be used, which has to be assessed in order to ensure cost-effectiveness (Hittinger et al., 2012). Considering the storage properties of li-ion batteries and Supercapacitors, the sensitivity analysis performed by (Hittinger et al., 2012) showed that capital cost, length of capital investment and efficiency have the largest potential in cost-of-service reduction. Still according to the same authors, peak shaving and frequency regulation are the most capital cost dependent energy services.

Providing energy services such as frequency regulation to the grid is becoming more necessary as the use of renewable energy increases. In 2010, the frequency regulation market was worth US$495 million. This is a new market for flywheels, which are fast-acting regulators, needing just a few seconds to perform frequency regulation, which makes them a more efficient regulator than major conventional power plants (Fairley, 2011). Moreover, battery-based frequency regulators based on fixed utilities, such as AES[1] in Johnson city-N.Y. or in electric vehicles infrastructures, which have a lower unitary cost, are one of the present biggest competitors of the flywheel (Fairley, 2011).

The various battery technologies are different not only on their physical layout, chemical composition and energy density, but also on their voltage and current output characteristics. As such, the power conversion interface may differ for each technology, and each will have unique time-varying output that must be matched. Other operational features, such as efficiency and size, also vary among technologies (Table 2-4).

Table 2-4 - Energy Storage System Characteristics(S. M. Schoenung, 2001)

Capital cost	**Operating features**	**Other technology-specific costs**	**Size**	**Siting issues**
Balance of Plant; Energy-related; Power-related.	Efficiency; O&M costs; Cycle or shelf life;	Parasitics; Replacement;	Storage equipment; Power conversion system.	Environmental Safety; Other features;

Despite being the weakest link of the energy domain, storage systems could play a very important role in maintaining system reliability, dynamic stability, enhanced power quality, transmission capacity and area protection (Ibrahim et al., 2008; F. Rahman et al., 2012; Ribeiro et al., 2001), presenting a positive cost and environmental impact by reducing fuel consumption and emissions through reduced line losses, and reducing the need of idle generation for frequency stabilization (H. Chen et al., 2009).

[1] Based Power firm AES - Frequency regulation facility with 22MW lithium batteries from A123 Systems with total cost of 22 Million US dollars.

2.1.3 Barriers to electric energy storage

The operation of battery based ESS is constrained in capacity and storage balances, for grid connections and batteries. According to Kristoffersen et al. (2011) and Kempton and Tomić (2005) the constraints include:

- nominal capacity of batteries;
- battery wear costs, related to the life cycle of each technology;
- capacity limits for the ESS connection to the grid, related to existing physical electric infrastructure interfaces, such as wires and other circuitry connection and/or the rated maximum power of the interface's power electronics.

One possible storage solution often referred in the literature is the EV storage infrastructure. However, it presents several limitations, namely: the unpredictability of vehicle (batteries) connection to the network, the uncertainty of the willingness of their users to present themselves as potential power providers, or the increase of harmonic and voltage problems, and of line losses, leading to a power quality degradation (Ipakchi & Albuyeh, 2009), (Gerkensmeyer et al., 2010), (Lopes et al., 2011). Therefore, the use of stationary systems can be seen as more predictable, enabling the grid manager to choose the most effective location of ESS in the network.

Ibrahim, Ilinca, and Perron (2008) pointed out the low durability for large-amplitude cycling as the main inconvenient, and Sovacool and Hirsh (2009) defends that a major issue to the adoption of a distributed storage infrastructure is also the existence of some resistance by network operators to integrate resources (e.g. batteries) which they do not manage.

Divya & Østergaard (2009) outline some of the reasons for a small deployment of storage systems such as the existence of a large number of conventional generators that can be adjusted to match the load demand (LD), and the interconnection of areas which can help to balance the LD. However, this scenario is changing due to the current high rate of deployment of renewable energy sources and the existing limits in the interconnections. Additionally, the lack of practical experience and availability of tools to perform optimization of operational costs, and to assess the benefits of storage technology (considering the market models) during planning, justify the motivation to develop such a methodology.

2.1.4 Economic ESS costs

The immediate success of battery ESS in rapid and short term applications is due to their capability of reacting instantly to system disturbances, which a conventional generator set cannot do (Divya & Østergaard, 2009). The mid-term battery ESS applications (less than 5 hours), based on dispersed ownership as in V2G applications, could become commercially viable if the utilities have a degree of control of the set of battery units in a way that make them useful to manage and control the power system, reducing operational costs. However, to make this idea feasible, an adequate framework needs to be developed (Divya & Østergaard, 2009), (Lopes et al., 2011), (Rocha Almeida et al., 2010).

Aiming at the economic viability of an ESS to provide a specific energy service, some authors argue that ESS should perform all the possible services in order to obtain the highest possible profit (Hittinger et al., 2012). The research and technological innovation is proposed as a key element for decreasing the capital costs, being the perception of technologies with greater potential for reductions in capital costs seen as essential to the future of ESS (Hittinger et al., 2012).

The valuation of associated costs and benefits of ESS may vary among authors, but some basic principles are used by all of them. Schoenung (2011) defined a general way to assess both costs and benefits of ESS. In the proposed method the capital costs (C_c) in [€] are the sum of power conversion ($Cost_{pcs}$) and the energy storage ($Cost_{storage}$) unit costs, as presented in equation (1).

$$C_c = Cost_{pcs} + Cost_{storage} \tag{1}$$

The power conversion unit costs are proportional to the power rating of the system as shown in equation (2).

$$Cost_{pcs}[€] = UnitCost_{pcs}[€/kW] \times P\ [kW] \tag{2}$$

The energy storage unit costs are proportional to the amount of energy stored (E) considering the round-trip efficiency[2] (η), as presented in equation (3).

[2] Round-trip efficiency is the ratio of total energy storage system output (discharge) divided by total energy input (charge), measured at the interconnection point.

$$Cost_{storage}[€] = UnitCost_{storage}[€/kWh] \times \frac{E\ [kWh]}{\eta} \tag{3}$$

The annualized capital costs (c_{ac}) are obtained by multiplying the total capital cost with a capital recovery factor (CRF), as presented in equation (4).

$$c_{ac} = C_c \times CRF \tag{4}$$

The CRF can be obtained using the equation (5) formula:

$$CRF = \frac{d(1+d)^n}{(1+d)^n - 1} = \frac{d}{1-(1+d)^{-n}} \tag{5}$$

where,

- d is the discount rate, dimensionless;
- n is the expected lifetime of the equipment in years;

The CRF converts the present value into a stream of equal annual payments over a specified time, at a specified discount rate, i.e., it is the ratio of a constant annuity to the present value of receiving that annuity during certain time.

Depending on the performed service, different parameters are used to assess the net benefit (subtracting the cost to the assessed benefits). Although with small differences, other authors aim to assess costs and revenues in a very similar way, as shown in Table 2-5 example.

Table 2-5 – Two perspectives for peak power service revenue and costs

Energy Service	**Peak power** (Lassila et al., 2012)	**Peak power** (Kempton & Tomić, 2005)
Revenue	$\boldsymbol{r = \Delta P_{peak} C_{inv}}$	$\boldsymbol{r = p_{el} E_{disp}}$
Cost	$\boldsymbol{c = \frac{C_{en} E_{charge}}{\eta} + (1-\eta) E_{charge} C_{grid\_en}}$	$\boldsymbol{c = c_{en} E_{disp} + c_{ac}}$

In equations shown in Table 2-5, c_{en} is the cost of each energy unit produced (delivered to network) [€/kWh], in Kempton and Tomic' (2005) p_{el} is the market rate (tariff) of electricity [€/kWh], E_{disp} is the total energy dispatched over the contract period [kWh], c_{ac} are the annualized capital costs [€/year]. Lassila et al. (2012) defined E_{charge} as the amount of electricity stored to battery [kWh], and C_{grid_en} the cost of delivered energy depending on the technology [€/kWh], C_{inv} is the average marginal cost (AMC) per year [€/kWh], ΔP_{peak} is the capacity increase [kW], and the η is the efficiency of the C/D cycle.

Kempton and Tomić (2005) present other expressions to quantify the costs and benefits for different services, based on the same general approach.

Table 2-6 - Revenues and costs presented by (Kempton & Tomić, 2005)

Energy Service	Spinning reserve	Regulation services
Revenue	$r = p_{el}E_{disp} + p_{cap}P_{disp}t_{disp}$	$r = p_{el}R_{d-c}P_{disp}t_{disp} + p_{cap}P_{disp}t_{disp}$
Cost	$c = c_{en}\left(\sum_{i=1}^{N_{disp}} P_{disp}t_{disp}\right) + c_{ac}$	$c = c_{en}R_{d-c}P_{disp}t_{disp} + c_{ac}$

In Table 2-6, R_{d-c} is the dispatch to contract ratio (dimensionless), measured according equation (6), t_{disp} is the time during which the power is dispatched [h], p_{cap} is the capacity price [€/kWh] and P_{disp} is the power of each dispachable storage unit [kW], P_{contr} is the contracted capacity [kW] and t_{contr} is the duration of the contract [h].

$$R_{d-c} = \frac{E_{disp}}{P_{contr}t_{contr}} \tag{6}$$

The inclusion of societal, environmental and technical contributions, when using ESS, could also be considered. Equation (7) shows one possible way to assess the benefit for peak power services, considering them at least equal to avoided grid reinforcements, using the EV available battery capacity (Lassila et al., 2012).

$$\text{Reinforcement} = C_{inv}\Delta P_{peak} \tag{7}$$

In equation (7), ΔP_{peak} is the power capacity decreased on the feeder [kW] and C_{inv} is the AMC on the feeder [€/kW].

In order to augment the ESS aggregated benefit, several authors propose to combine the associated impacts with more or less overlapped benefits as shown in Figure 2-4.

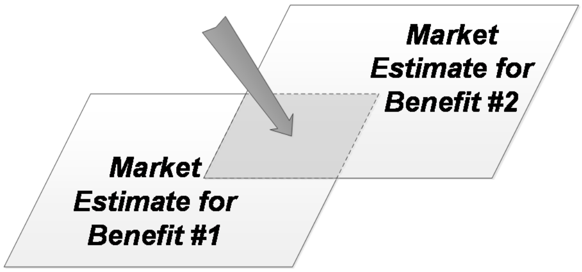


Figure 2-4 - Market Estimation for Combined Applications/Benefits: Market Intersection (Eyer et al., 2004)

In many cases more than one advantage is required from storage for benefits to exceed costs. However, careful consideration of operational, technical, and market details is required before considering all the possible benefits. Operational objectives involve conflicting uses for storage, e.g. between power output and duration of delivery (Eyer et al., 2004).

In some cases ESS are physically unable to serve more than one need. As an example, ESS are unable to simultaneously tolerate frequent deep discharges and/or significant cycling. Storage systems well suited to the transmission and distribution upgrade deferral applications, are probably not suitable for energy price arbitrage [3](Eyer et al., 2004).

Another example is when storage cannot respond very rapidly to changing line conditions. Such systems may be suitable for energy arbitrage or to reduce demand charges but may not be able to provide transmission support or end-user power quality benefits.

Eyer et al. (2004) provides a summary of key standard assumption values used for evaluating benefits, market potential, and total economic benefits from storage used for specific applications and/or for specific benefits, as shown in Table 2-7.

[3] Advantage from buying and selling energy in different market price periods

Table 2-7 - Summary of Key Standard Assumptions and Calculations for Applications of Storage in the State of California (Eyer et al., 2004)

Application/Benefit	Discharge Duration*		Lifecycle Financial Benefits ($/kW)	Maximum 10-year Market Potential (MW)	Ten-year Economic Benefits ($Million)**
	Minimum	Highest			
Bulk Electricity Price Arbitrage	1	10	200 to 300	735	147 to 220
Central Generation Capacity	4	6	215#	3,200	688
Ancillary Services	1	5	72***	800	58
Transmission Support	2 Sec.	5Sec.	169	1,000	169
Reduce Transmission Access Requirements	1	6	72***	3,200	230
Transmission Congestion Relief	2	6	72***	3,200	230
Distribution Upgrade Deferral 50th Percentile of Benefits	2	6	666#	804	536
Distribution Upgrade Deferral 90th Percentile of Benefits	2	6	1,067#	161	172
Transmission Upgrade Deferral	4	6	650#	1,092	710
Time-of-Use Energy Cost Management	2	see tariff	1,004	4,005	4,021
Demand Charge Management	6	11	465#	4,005	1,862
End-user Electric Service Reliability	0.25	5	359#	4,005	1,438
Electric Service Power Quality	10 sec.	1 Min.	717#	4,005	2,872
Renewables Capacity Firming	6	10	172##	1,800	310
Renewables Contractual Time-of-Production Payments	6	10	655##	500	328

*Hours unless other units are specified.
**Over ten years, based on lifecycle benefits times maximum market potential (market *estimates* will be lower).
***Placeholder values. The actual benefit was not estimated.
#Does not include incidental energy-related benefit. ; ##Wind generation.

Whenever possible, it is very important to assess the AMC of a specific ESS, since the procedures of current energy markets are used to define which units are the first to provide services to the network. In order to provide data on the cost of selected storage technologies some guidance is presented in Table 2-8. The exact information depends on the manufacturer, the application and usage. However, it is a good basis for establishing some assumptions in further studies.

Table 2-8 - Capital and O&M costs of selected technologies(J. Vasconcelos et al., 2012)

Technology	Capital costs		O&M Costs
	Power conversion (€/kW)	Storage unit (€/kWh)	Fixed O&M costs (€/kW.year)
PHS	900	56	
CAES	520	4	
Advanced Pb-acid batteries	300	250	
Pb-acid batteries with carbon-enhanced electrodes	300	250	
Li-ion batteries	300	450	
NaS batteries	260	260	30-40
ZEBRA batteries	400-500		
ZnBr batteries	300	300	
VRB batteries	300; 1750	450; 215	40,000 (1MW/6h)- 230,000 (10MW/6h)b
Flywheels (high speed composite)	450	1195	
Supercapacitors	370	7470	

It should be noted that the DEESS evaluation impact is not indifferent to the technology considered. Moreover, S. M. Schoenung & Hassenzahl (2003) also argue that the real benefit should be assessed considering the distribution of ESS in the network, given a specific technology and considering market parameters, such as electricity costs and interest rates. Finally according to Lassila et al. (2012), the ESS management can be more effective if the network operator owns the storage system.

2.2 Assessment methodologies

Previous research assessing the impact of energy storage systems (ESS) on the power system operation and economics has been focused on economic/optimal sizing. As such, ESS have been modelled from the point of view of cost (economic models) or with a focus on the assessment of operational benefits, modelling the ESS response to power system disturbances at appropriate time scales or operational models, as shown in Table 2-9 (Divya & Østergaard, 2009).

Table 2-9 –Battery ESS models for economics and power systems studies (Divya & Østergaard, 2009)

BESS models used for economic analysis	BESS models for power system studies
▪ Utility side applications;	▪ BESSpower system reliability analysis;
▪ Demand side applications.	▪ BESSpower system stability analysis.

The majority of studies performing economic analyses of ESS considered vertically integrated utilities, not incorporating market models to assess the benefits of ESS for the current deregulated market. From the operational side, most studies on the impact on power systems generally do not refer to any particular battery technology, or to any limitation of the performance of ESS (Divya & Østergaard, 2009). Nevertheless, some authors have included technology characteristics in their models (Fossati et al., 2015), (Dufo-López & Bernal-Agustín, 2015).

Focusing on the economic side, some authors presented methodologies for evaluating the associated costs and benefits of energy storage by analyzing single specific services (S. Schoenung, 2011), (Kempton & Tomić, 2005). However, none of these studies consider the relation of an ESS management scheme with its associated impacts on the electric grid performance.

Aiming to increase wind farms power dispatchability (power firming) Le and Nguyen (2008) developed an analytical approach to find a rating for the most-profitable ESS. Some of the considered benefits were the revenue from higher renewable integration into the network (higher capacity), the revenue from generation capacity firming, the revenue from improved grid voltage stability, the revenue from improved grid reliability and the revenue related to environmental benefits such as reduced greenhouse gas(GHG) emissions. Those authors also concluded that the quality of results depends on the measurement and verification methods, and on the accuracy of the calculation methods, which should be established within the research community and the power industry.

Concerning operational benefits, the advantages of ESS led to the development of the V2G concept, a long-held idea of an option to provide specific energy services to the grid based on connected EVs capacity. Different methodologies were then applied to analyze their contribution to the grid (Lassila et al., 2012), (Lopes et al., 2011), (Kristoffersen et al., 2011), (Balcells & Garcia, 2010). However, the uncertainty associated with the location of EV led some authors to focus on this constraint (Battistelli et al., 2012). To assess the possible contribution in terms of energy exchange to the electricity network, Lassila et al (2012) tested the effect of different C/D management schemes to provide specific energy services.

Considering the technical characterization requirements to perform power services studies (e.g. regulation services), some authors have used island case studies or simplified grid models to ease the application of those methodologies (Sigrist et al., 2013), (Almeida et al., 2011), (Lim et al., 2011).

As mentioned previously, most studies in the literature focused on only one type of assessment (either technical or economical), and usually did not provide more than one option for a DM. However, effective decisions over the subject will need to simultaneously consider both kinds of objectives (and even different objectives of each kind), and should imply a multiobjective optimization procedure.

Le et al (2012) presented a multiobjective methodology for calculating a reference output profile, using a C/D scheme for guiding the ESS operation, together with an economic assessment for compensating wind power variation through storage, and an optimization-based method for determining the ESS optimal rating. Regarding the technical side, and envisaging to fill the gap between the real and the desired profiles, these authors used an optimum power flow analysis (OPF) program to define a suitable storage power output for a given network. Regarding the economical side, they determined the ratings of the ESS by an optimization-based method, considering a cost-based objective function that maximizes the net benefit and takes into account five possible benefit factors, namely the revenues earned from: saving and integrating an amount of wind power into the grid, wind farm capacity firming, improved voltage stability, improved reliability, and environmental considerations.

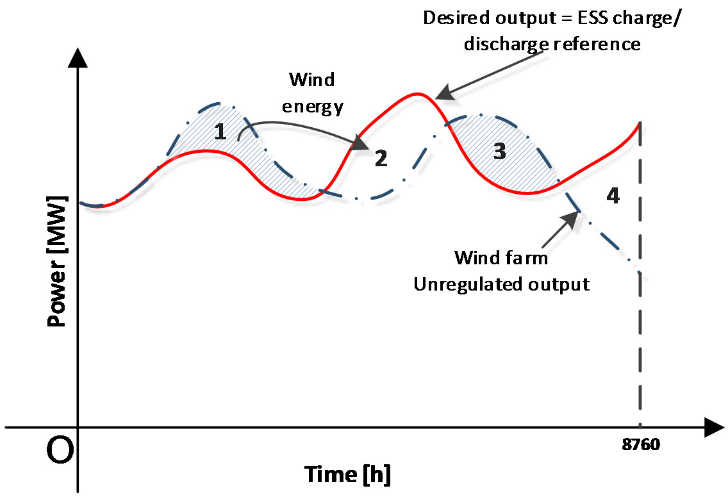


Figure 2-5 – Illustration of simplified wind output profile and desired output (Le & Nguyen, 2008)

Recent multiobjective methodologies, based on different strategies, have been developed to obtain the most suited daily profile of the state of charge of batteries (whose locations depend on the average loads of network buses), minimizing (i) the energy losses in the electric network, (ii) the total electricity generation cost and (iii) the GHG emissions (Ippolito et al., 2014).

Table 2-10 – Literature review regarding ESS working schemes.

Articles	Objective	Working principles
(Le et al., 2012), (Le & Nguyen, 2008)	Wind Power penetration and cost analysis	Reference power output and remaining energy for energy services.
(Lassila et al., 2012)	Methodology to estimate energy storage feasibility	Considering the technical limits and load diagram
(T. Chen et al., 2013)	Method to evaluate advantages of ESS.	Based on energy rates
(Koyanagi & Uriu, 1998)	Time shift method for time control	Considered time patterns of use
(S. Rahman & Shrestha, 1993)	Analysis of impact method on the distribution system	User defined periods based on technical data.
(Nguyen et al., 2012)	Framework for determining the optimal charging/discharging of BES	Using predicted production profiles valued with day-ahead and real-time prices
(Ippolito et al., 2014)	Definition of some stratagies for design and the optimized management of ESS	Multiobjective optimization using different design strategies

Table 2-10 summarizes the approaches used in the literature in order to establish the operating scheme of storage units. Modified profiles are commonly used to assess the impact of C/D batteries (e.g. EVs) in the power grid, or evaluating impacts on load diagrams (T. Chen et al., 2013; Koyanagi & Uriu, 1998; Lassila et al., 2012; Le & Nguyen, 2008; Le et al., 2012; Leou, 2012; Nguyen et al., 2012; Qian et al., 2011; S. Rahman & Shrestha, 1993). In order to avoid new peaks, S. Rahman and Shrestha (1993) and Koyanagi and Uriu (1998) proposed the need of proper incentives and market regulation. Both the creation of limits to use the excess energy available, according to grid requirements and the time shift control, regulating the charging schedules in the network, were presented as adequate mechanisms to avoid new network power peaks.

As already stated, other ESS advantages are the ability to postpone grid reinforcements, to avoid short interruptions and voltage quality problems, to shave power peaks and to smooth load curves (Lassila et al., 2012). However, the economic attractiveness of ESS is not guaranteed, especially due to the high capital cost (when compared to alternative technologies). Therefore, the proposal of a feed-in tariff scheme is justified to increase the interest of investors (Dufo-López & Bernal-Agustín, 2015).

The main obstacle to ESS deployment seems to be the corresponding investment costs and the reluctance of network operators to integrate resources that they do not manage (Sovacool & Hirsh, 2009). To overcome these barriers, it is crucial to improve the assessment of application and benefits of these systems, namely by developing operational tools to select the quantity and location of these resources, optimize the operational cost and assess the benefits of storage during the planning phase (EPRI, 2010), (Divya & Østergaard, 2009).

Drawing on the existing literature, several potential simulation tools for network analysis may be applied, considering distribution networks, EVs and energy storage applications.

Table 2-11 - ESS studies applying potential simulation software tools

Article	Used Software Program	Analysis Type	Objective
(Lopes et al., 2011)	PSSE software Matlab/simulink	Steady-state and power flow analysis	Conceptual framework to integrate electric vehicles
(Rocha Almeida et al., 2010)	Plansys software	Dynamic simulation of power systems	Study the impact of EV in the automatic generation control operation
(Balcells & Garcia, 2010)	MATLAB – Simulink and the toolbox Sim Power Systems	Harmonic analysis	Establish a design guide for parking facilities.
(Cvetkovic et al., 2009)	LabVIEW	Power flow analysis	Presents the concept of a future home uninterruptible renewable energy system with V2G technology implementation.
(Dyke et al., 2010)	Mathworks Matlab Simulink	Load flow analysis	Establishes a series of well-defined electric vehicle loads that are subsequently used to analyze their electrical energy usage and storage in the context of more electrified road transportation.
(Pieltain Fernandez et al., 2011)	Reference Network Model from Regulators	Power flow analyses.	Give a comprehensive approach for evaluating the impact of different levels of PEV penetration on distribution network investment and incremental energy losses.
(Koyanagi & Uriu, 1998)	Generic	Mathematical modeling	Propose a positive utilization of the electric vehicles for load leveling
(Kristoffersen et al., 2011)	Generic	Framework	Presents a mathematical programming model for optimal charging and discharging of the electric vehicles
(Moses et al., 2010)	Matlab (DHPF- Decoupled harmonic power flow)	Load flow analysis	Highlights and demonstrates potential power quality problems that can occur in a smart grid operating with Plug-in Electric Vehicles
(Pillai & Bak-Jensen, 2010)	DIgSILENT	Load flow analysis	Investigates the impacts of increasing EV loads in a typical Danish primary distribution network
(S. Rahman & Shrestha, 1993)	Generic	Mathematical modeling	Investigate the impact of EV load on the electric utility distribution system.

Table 2-11 summarizes a selection of studies applying potential software tools. In most studies, load power flow analysis was combined with power demand profiles of the distribution grid to quantify the technical impact of each solution. In order to assess the best location, avoiding pre-defined scenarios, the use of techniques that can combine grid characteristics, load diagrams, supply diagrams and C/D diagrams of ESS, will be important to obtain the maximum benefit from storage. Leou (2012), and T. Chen et al. (2013) used genetic algorithms (GA) whose results only differ in the fitness function factors. The use of GA enables a multiobjective approach especially useful to problems that do not have a unique optimal result but a set of non-dominated or efficient solutions (the choice depending on the relative importance of each objective to the DM).

As a result of using a multiobjective approach the possible use of interactivity should be explored, helping the DM to obtain the desired results without the need to map his/her preferences to hard values assigned to weights of each objective function (Gonçalves et al., 2013).

2.2.1 Evaluation objectives

Table 2-12 lists a set of studies from the literature[4], identifying the most often used objectives when evaluating ESS, and optimization techniques, including the use of genetic algorithms. Depending of the scope and application, different arguments can be used to select evaluation criteria.

Table 2-12 – Summary of energy storage assessment issues referred in the literature.

Article	Considered issues	Technique
(T. Chen et al., 2013)	▪ Electric Fee Saving; ▪ Line Loss Reduction; ▪ Average Voltage Deviation.	Multiobjective optimization algorithm
(Leou, 2012)	▪ Energy price arbitrage; ▪ Reducing transmission access cost; ▪ Facility investment deferral; ▪ Investment cost; ▪ Operating and maintenance cost.	Genetic algorithm with linear programming
(Lassila et al., 2012)	▪ Investment costs of the network; ▪ Operational costs of the network; ▪ Investment costs of the energy storage; ▪ Operational costs of the energy storage.	Methodological framework
(Miyauchi & Tashiro, 2009)	▪ Reactive Power Supply Index; ▪ Transmission Loss Reduction Index; ▪ Bus Voltage Sustainability Index.	Evaluation method
(Sahoo & Prasad, 2006)	▪ Voltage stability.	Fuzzy genetic approach

In the multiobjective approaches presented in Table 2-12, all authors presented fitness functions where the objectives were equally weighted. The main difference between studies regarded the used objectives to perform the impact evaluation.

More concern with economic aspects, (Lassila et al., 2012; Leou, 2012) focused their assessment in the associated benefits from charged and discharged energy, between ESS and the network, in different time periods. Leou (2012) additionally included the economic benefits from reducing the transmission access costs and from deferring facility investments. Moreover, both authors considered the investment costs and the maintenance costs of the ESS and for the network.

[4] A broader analysis could be found in (Lassila et al., 2012)

The use of network data not easily available, and in some cases restricted, such as the investment and maintenance cost of the network or the benefits from deferring facility investments turn those objectives difficult to use.

T. Chen et al. (2013) developed a multiobjective methodology that enables the use of public available or easy to obtain data, to assess the ESS impact from the point of view of the network operation. The electricity fee saving was assessed by subtracting the costs of the stored energy from the revenues resulting from selling during higher market prices periods. Different scenarios of losses and average voltage deviations are compared with the reference network (without storage) to assess the impacts of DEESS on line loss reduction and average voltage. However, the use of a fitness function where all objectives have the same representativeness restricts the assessment of individual objective impacts.

Also considering equal weights for the three objective functions Miyauchi and Tashiro (2009) performed a technical assessment of the reactive power value using the transmission losses, the voltage stability and the reactive power supply of conventional generators as performance indices.

Finally, and focused on network reconfiguration Sahoo and Prasad (2006) developed a fuzzy genetic approach using only the voltage stability index to assess the technical impact on the network.

Drawing on the literature review, one can conclude that investment and operation costs, together with energy tariffs, are important factors for the economic analysis and voltage stability, as well as active power losses are important factors for technical analysis.

2.3 Multiobjective optimization and genetic algorithms

A diversity of methodologies have been used for solving optimization problems, leading the classical mathematical operations towards a knowledge based on human behavior intelligence and Nature. Evolutionary algorithms (EA) are one of the solutions developed to combine search techniques and optimization. Inspired on natural evolution mechanisms and genetics, the EA works with several solutions simultaneously, providing a set of individuals generally designated by population. By applying the algorithm, a set of individuals with a starting low rate of survival or environmental fitness, can evolve over several generations. Based on nature evolution process, the most fit individuals are retained by natural selection passing their traits to the next generation, combining features in so-called offspring, or leading to new specimens through a mutation process that change their characteristics for better environment adaptation.

Most of the real problems usually involve multiple objective optimization and decision making, and engineering is one of the areas where the existence of conflictive objectives is most likely to appear, causing limitations on one or more objectives and associated difficulties in the optimization process. The ability to work with a population of potential conflictive solutions in every generation, enables EA to effectively solve many real problems, as shown its wide application in the literature.

An operational optimization tool that comprises a search technique for exact or approximate solutions, based on the evolution of organisms, is the Genetic algorithms (GA), which belong to the larger class of EA.

2.3.1 Improved NSGAII

GA have been widely used in several fields, such as economic dispatch, reconfiguration of power networks, optimal placement of capacitors or inductors, and optimal power flow analysis (T. Chen et al., 2013). Conventional GA, however, may get stuck at a local optimum, or have slow convergence speed. In order to overcome these shortcomings, many researchers have aimed to improve the performance of GA (R. M. Vitorino et al., 2009), (Sahoo & Prasad, 2006), (J. A. Vasconcelos et al., 2001).

A GA multiobjective approach allows the integration of different non correlated objectives, but the existence of multiple conflicting objectives prevents the achievement of an optimal. In such a case, the DM has to analyze a set of non-dominated solutions, or solutions which are no worse than all others at least in one aspect (objective) in order to establish tradeoffs and to choose the option that better represents his/her preferences.

The Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is a particular case of a multiobjective GA implementation which has proved to be efficient, especially in power distribution operation and planning problems. Detailed information regarding the working principle of this tool can be found in (Deb et al., 2002).

GA use genetic operators, such as crossover, cloning and mutation, to perform genetic manipulation in order to generate new individuals with characteristics of both parents.

An improved NSGA-II (iNSGA-II) was proposed in (Romeu M Vitorino et al., 2013), replacing the fixed genetic operators of conventional NSGA-II with a dynamic adaptation of crossover (*pc*) and mutation (*pm*) probabilities, according to the genetic diversity in the population. The advantages of the method are further described in (R. M. Vitorino et al., 2009), (R.M. Vitorino et al., 2013).

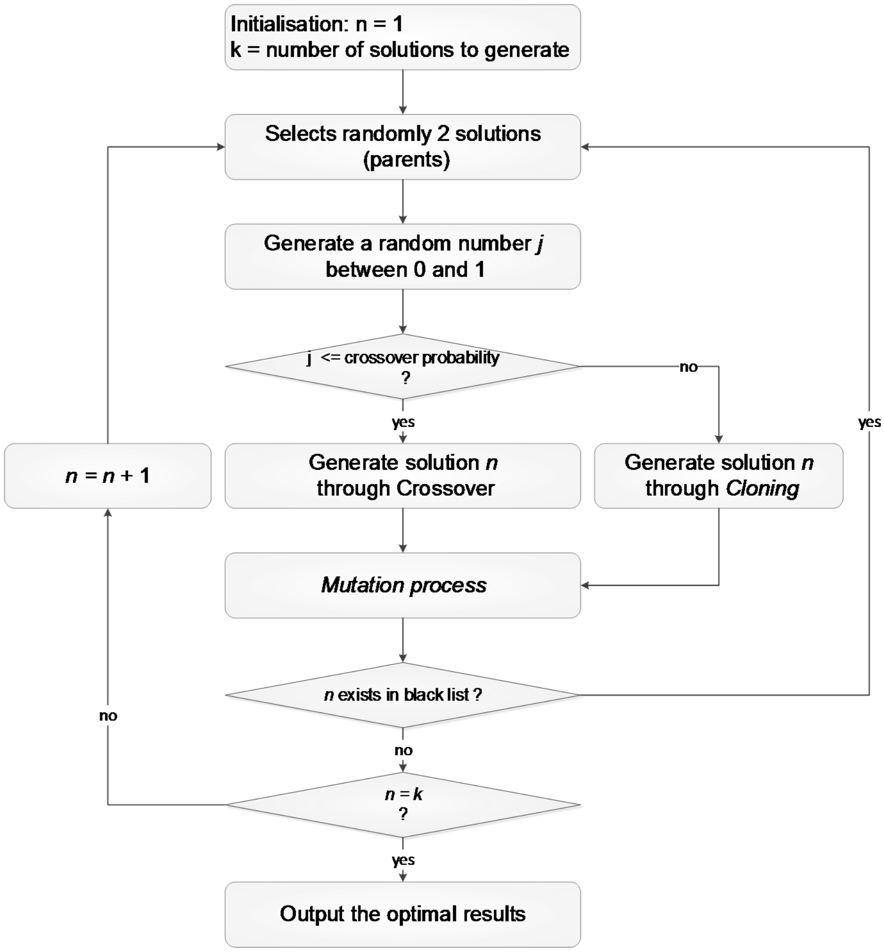


Figure 2-6 – Genetic manipulation process of IGA (Romeu M Vitorino et al., 2009).

Figure 2-6 presents a flowchart on the genetic manipulation process used in IGA. Usually the crossover operator is predominant (thus with a higher probability of occurrence) and the mutation operator has a low probability. However, the mutation operator is highly significant, because it is the operator which is responsible for introducing new genetic characteristics in the population. This operator randomly changes characteristics of one specific individual, avoiding a premature convergence and guarantying a non-null probability of reaching any point of the search space. Therefore, each time the genetic characteristics tend to become homogeneous, an attempt to increase diversity is made by increasing the mutation probability.

In order to improve the computational efficiency and accuracy of the search tool, a black list of infeasible solutions was used to record all the individuals whose characteristics could imply negative impacts beyond the admissible limits.

The choice of crossover and mutation probabilities (*pc* and *pm*, respectively) affects the behavior and performance of the GA (Romeu M Vitorino et al., 2009). The heuristic updating principles of the pc and pm probabilities, as a function of the genetic diversity (Gdiv) are as follows:

1. Use large *pc* and small *pm* when G_{div} in the current generation is large;
2. Use small *pc* and large *pm* when G_{div} in the current generation is small.

pc and *pm* are adjusted according to the following conditions, presented in (8) and (9), and considering bounds B_{min} and B_{max}:

$$pc = \begin{cases} pc_{min}, if\ G_{div} < B_{min} \\ pc_{max}, if\ G_{div} > B_{max} \end{cases} \quad (8)$$

$$pm = \begin{cases} pm_{max}, if\ G_{div} < B_{min} \\ pm_{min}, if\ G_{div} > B_{max} \end{cases} \quad (9)$$

If the genetic diversity (G_{div}) is within the considered bounds, pc and pm are calculated through a linear interpolation as shown in equations (10) e (11).

$$pc = \left(\frac{pc_{min} - pc_{max}}{B_{min} - B_{max}}\right) G_{div} + \left(\frac{pc_{max}B_{min} - pc_{min}B_{max}}{B_{min} - B_{max}}\right) \quad (10)$$

$$pm = \left(\frac{pm_{max} - pm_{min}}{B_{min} - B_{max}}\right) G_{div} + \left(\frac{pm_{min}B_{min} - pm_{max}B_{max}}{B_{min} - B_{max}}\right) \quad (11)$$

Promising results were presented in (R.M. Vitorino et al., 2013), (R. M. Vitorino et al., 2009) supporting this approach (when compared to conventional GA or particle swarm optimization (PSO) algorithm) in terms of speed of convergence and stability, for an application on network reconfiguration problems as shown in Figure 2-7.

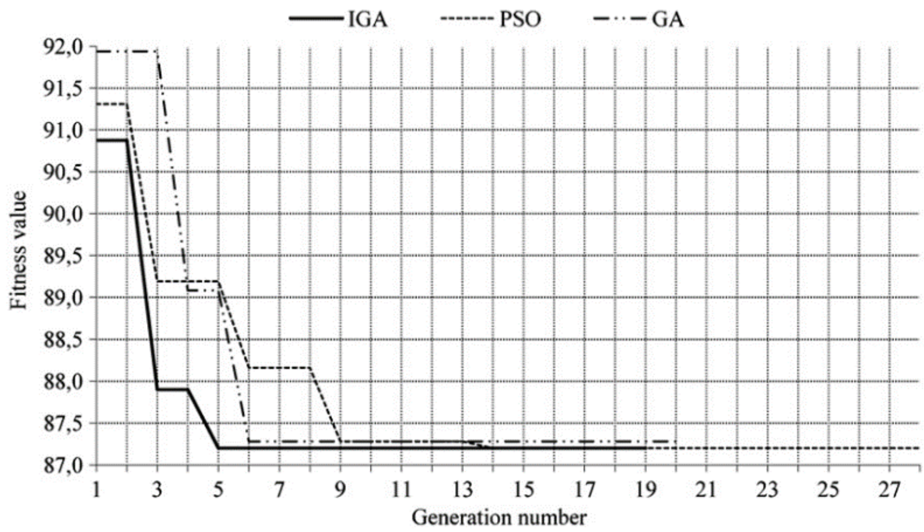


Figure 2-7 - Convergence performance using IGA and other methodologies (R.M. Vitorino et al., 2013)

Regarding both the good results presented by R.M. Vitorino et al. (2013) and the performance test results obtained by the author Gonçalves et al.(2013) exhibited in Figure 2-8, the decision was to use this approach for the assessment of the best location of distributed electric energy storage units.

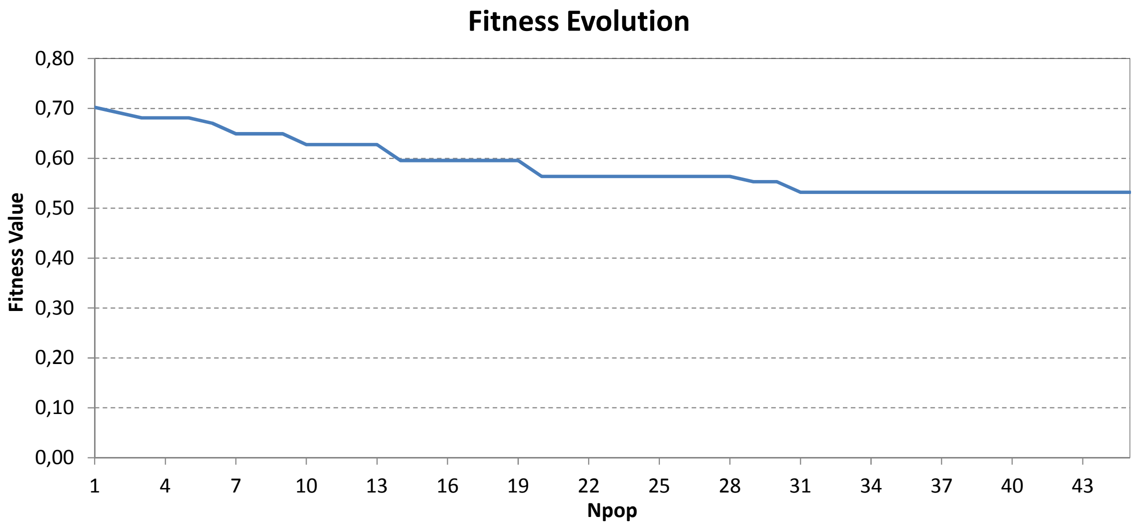


Figure 2-8 - Evolution fitness results of IGA as a function of the number of generations (Npop) (Gonçalves et al., 2013)

2.3.2 Genetic diversity in the population

The genetic diversity of a population, i.e., the genetic variability of individuals, is responsible for the dispersion of solutions in the feasible space. To measure the resemblance of individuals, they must be regarded as multidimensional vectors and a distance calculated from one vector with the differences may be used. If the distance is below a predefined threshold (Dth), one may assume the two individuals are similar; else, the two individuals are dissimilar (R. M. Vitorino et al., 2009).

$$d(i,j) = \sqrt{(g_i(1) - g_j(1))^2 + \cdots + (g_i(N) - g_j(N))^2} \qquad (12)$$

Where g_i is the chromosome gene of individual "i" and g_j the chromosome gene of individual "j".

To measure the genetic diversity (Gdiv), the following equation is used:

$$G_{div} = \left(\frac{\sum_{i=1}^{Nind} \sum_{j=i+1}^{Nind} 1_{\{d(i,j)>Dth\}}}{N_{ind}} \right) \times 100 \qquad (13)$$

G_{div} it is a variable in the range [0,100] meaning that when the value is zero all individuals are similar and when it is 100 all individuals in the population are dissimilar.

2.3.3 Selection mechanism

The selection mechanism on iNSGA-II is performed using a "Binary Tournament Selection" based on rank and crowding distance. An individual is selected if its rank is lower than the rank of the other or if its crowding distance is greater than the crowding distance of the other, in case they share the same rank.

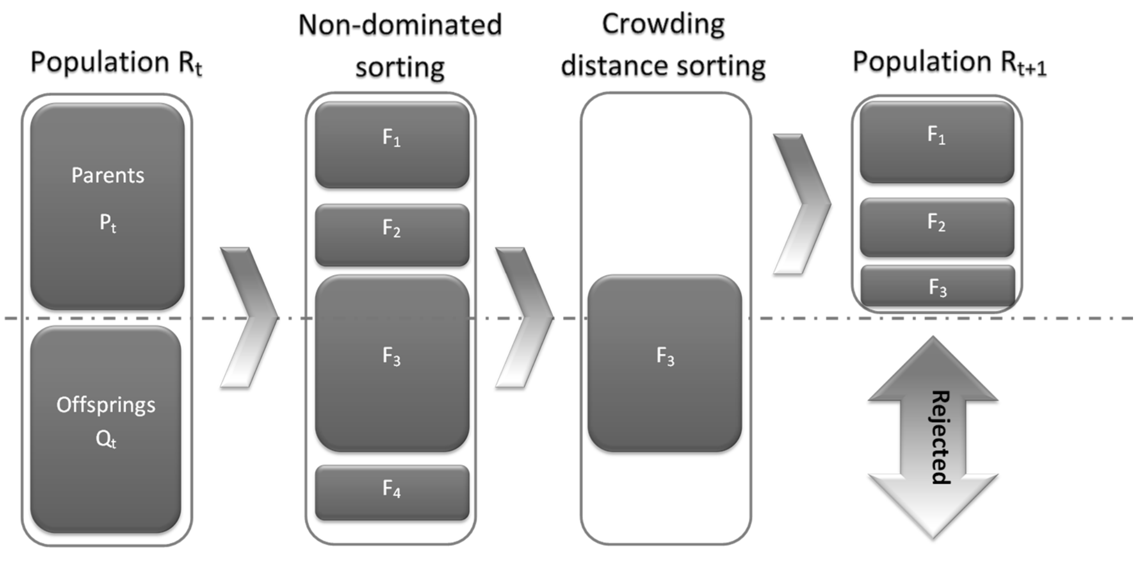


Figure 2-9 – NSGA-II procedure

Parents are selected using non-domination, with assigned crowding distance, expressed through the crowded-comparison-operator ($\prec_n$) that provides a fast and easy way to estimate the spread in obtained solutions (Deb et al., 2002).

The crowded-comparison-operator provides the estimation of the perimeter of the cuboid formed using the nearest neighbors as the vertices. This operator will provide the needed information to choose regions with lesser density. The comparison is carried out in two steps for every individual i in the population:

1. Assignment of non-domination rank (i_{rank});
2. Assignment of crowding distance ($i_{distance}$) for individuals on the same front: The crowding distance represents the sum of absolute normalized differences in the function values of two adjacent solutions. For boundary solutions, namely solutions with smallest and largest function values, an infinite distance value is assigned.

Considering the non-domination rank (i_{rank}) and the crowding distance ($i_{distance}$) the partial order for the crowded-comparison-operator ($\prec_n$) is:

$$\begin{aligned} i \prec_n j \text{ , } If \ (i_{rank} < j_{rank}) \\ or \ \ i_{rank} = j_{rank} \\ and \ i_{distance} > j_{distance} \end{aligned} \tag{14}$$

Since all individuals are included in population “R_t” by using the binary tournament selection with crowding-comparison-operator, elitism is ensured.

2.3.4 Multiobjective optimization and decision making support

A multiobjective analysis comprises two phases: the search and the decision making. The first refers to the optimization process, namely the search for a set of suited solutions, considering the problem formulation. Secondly, based on the obtained possible solutions, a tradeoff between objectives must be performed by the DM.

In the first phase, in order to introduce the DM preferences in the optimization process, different approaches can be applied. According to the moment when the DM is consulted, they all could be fitted in three main types; *a priori*, *a posteriori*, or interactively during the search (Iris & Asan, 2012).

The *a priori* methods lead the search to a focalized Pareto Frontier, since the DM preferences are embedded in the GA to bias the search towards the preferred region. Due to the need of assigning the preference trade-offs on the objective values, this approach could be more difficult as the number of objectives increases, or if the DM has no experience in the specific multiobjective problem (Iris & Asan, 2012) (e.g. specific expectations).

Considering the *a posteriori* approach, the DM decides whether to aim for the solution closest to the ideal point (i.e. which optimizes all the objectives simultaneously), or to apply his preferences on the objective functions results in order to identify his preferred solution or set of solutions. The *a posteriori* approach has the advantage of reducing the final number of solutions on the Pareto Frontier (Iris & Asan, 2012). However, it has the difficulty of presenting to the DM a set of possible solutions from which to choose, instead of a single "optimal" one, as well as the associated computational effort in generating a large set of non-dominated solutions (Klamroth & Miettinen, 2008).

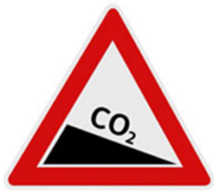
The *interactive methods* help to overcome the above-mentioned constraints enabling the DM to learn about the problem, its possibilities and limitations, as well as the interdependencies among the objective functions (Klamroth & Miettinen, 2008). These methods can be applied to decision making or optimization processes in which the preferences are interactively refined at interleaved steps (Kacprzyk; & Pedrycz, 2015). However, it may be worth to first get an overview of what the Pareto set looks like, in order to acknowledge the feasibility of solutions (Klamroth & Miettinen, 2008).

The available methods to introduce the DM preferences in the optimization process are not conflictive and each has advantages and limitations. Moreover, the potential of combining these tools and approaches enable to develop hybrid approaches, with better performances when solving multiobjective optimization problems (Klamroth & Miettinen, 2008), (J. Clímaco & Antunes, 1994).

In the second phase the final selection of non-dominated solutions from the Pareto Set might be a difficult task, mainly due to the fact that the set of available solutions, and the corresponding representative Pareto Frontier in the objective function space, may be crowded (Iris & Asan, 2012).

2.4 Externalities: CO2 impact evaluation

Assessing externalities can be a very difficult task. In fact, all the issues regarding environmental impacts are critical due to the difficulty to monetize them, as the environment and its resources are generally considered abundant, renewable, without boundaries and free of charge.



Many authors aimed to minimize environmental impacts by assessing not only their emissions but also the linkages between acquisition and consumption, giving a price to the associated greenhouse gas (GHG) emissions and welfare loss (Paltsev et al., 2008), (Milne et al., 2013), (Grant et al., 2006), (Commission, 2005). A well-known example is the ExternE methodology (Commission, 2005) , which comprises a framework to transform different impacts into a common unit, using specific conversion factors (Neves, 2004).

The difficulty to implement and quantify impacts resulted in many methodologies being unused, such as the ExternE methodology, replaced to some extent by the CO2 equivalent valorization within the European emissions trading system (EU ETS). The CO2 equivalent is an internationally recognized term, used by the Kyoto protocol (Ki-moon, 2008) to describe different GHG in a common unit, enabling their comparison in terms of their global warming impact. As a tool to help accomplishing the Kyoto protocol targets, the EU ETS is the first (and still the largest) international system for trading GHG emission allowances, covering 28 EU countries.

The EU ETS sets a cap (or limit) on the total amount of GHG emissions that can be emitted by factories and reduces the cap over time, so that emissions fall. Despite its limitations, this approach is under consideration among several non-European countries (and countries which did not ratify the Kyoto protocol for political or economic reasons) (Paltsev et al., 2008), (Commission, 2015d).

Launched on the 1st January 2005, the initial trading period ran for three free trading preparation years in a “learn by doing“ process. Since initial emission projections revealed to be wrong, the first phase enabled to assess the correct allocation of allowances among member states and sectors. After this period, and using the assessed data under the EU ETS, the second phase began on the 1st January 2008 (until the end of 2012), matching the first commitment period of the Kyoto Protocol.

In order to guarantee the EU as a whole, as well as each individual member state Kyoto commitments, the EU ETS emissions cap had been settled 6.5% below 2005 levels. The second phase showed that harmonization (regarding the cap on overall allowances settlement) within the EU ETS is imperative to guarantee the EU emission reduction objectives at least cost and with minimum competitive distortions (Commission, 2015d).

With a timespan of eight years, the third stage started on January 2013, and introduced a more efficient, harmonized and fair system. The cap was settled in less 21% of emissions compared to 2005 and the amount of auctioning is expected to be more than half. A single EU-wide cap was introduced and allowances are now allocated on the basis of harmonized rules, avoiding the need of national allocation plans (used in phases 1 and 2). The cap was settled considering the average total quantity of allowances to be issued by member states in phase 2, the broadened scope of the system that was introduced in phase 3, and the overall reduction of GHG emissions, compared to 1990. Considering the target EU emissions reduction, the EU defined a wider cap, as follows (Commission, 2015d):

- 21% reduction in EU ETS sector emissions (compared to 2005 by 2020);
- Reduction of approximately 10%, compared to 2005 for the sectors that are not covered by the EU ETS.

Due to its effectiveness on promoting the reduction of GHG emissions, as well as searching a cost reduction of cutting emissions (increasing the market liquidity and making the carbon price more stable), the EU ETS is currently being integrated with another cap-and-trade systems. This will enable participants to comply with their obligations in a more cost effective way, promoting a global cooperation on climate change, and leveling the international playing field (Commission, 2015d).

Even with adjustments in the market rules (as a result of stage 1 and 2 learning process), there is a surplus of allowances since 2009, affecting the orderly functioning of the carbon market (e.g. excessive reduction in the carbon price). As a result, the commission postponed the auctioning of 900 million allowances until 2019-2020. The impact analysis regarding this option showed the ability to rebalance supply and demand in the short term, as well as to reduce price volatility without compromising competitiveness (Commission, 2015b). Moreover, the commission proposed to make a structural change in the ETS in the long term, establishing a market stability reserve. This reserve would address the present surplus of allowances, improving the system resilience (Commission, 2015b).

In spite of its pros and cons, the EU ETS is part of a continuous progress towards a low-carbon society which objectives are to cut emissions to 80% by 2050 compared to 1990 levels (with intermediate milestones of 40% by 2030 and 60% by 2040) (Commission, 2015b).

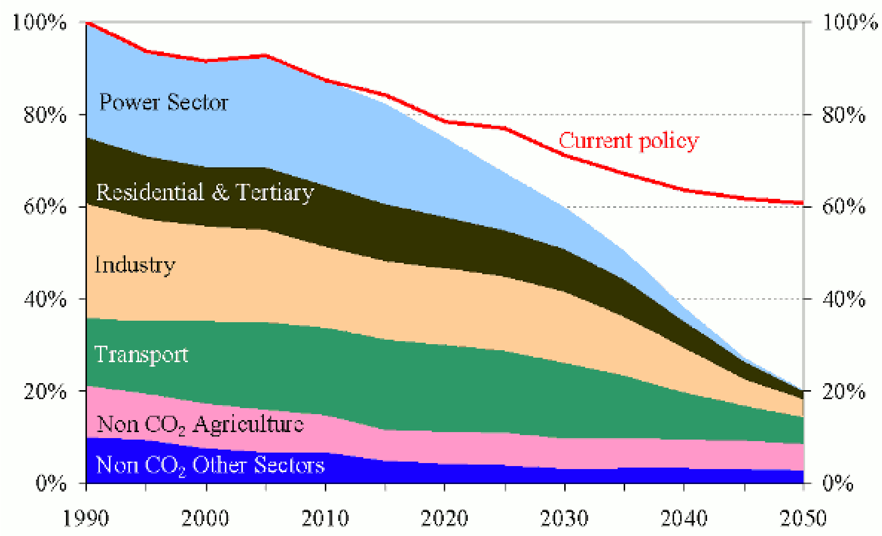


Figure 2-10 – Possible 80% cut in GHG emissions in the EU, using year 1990 as reference (Commission, 2015b)

Figure 2-10 shows both the initial (and current) EU policy objectives endorsed in the “2030 climate & energy framework” and the more ambitious presented in “2050 low-carbon economy”. The EU 2050 targets considered the almost total elimination of CO_2 associated to the power sector, by replacing fossil fuels in transport, heating and by promoting electricity production from renewable sources, together with the capture of CO_2 in fossil fuel power plants and a strong investment in smart grids, as detailed in (Commission, 2015a). For transportation and building sectors, the cuts are expected to achieve almost 60% and 90%, respectively, by increasing efficiency in current technology, replacing current vehicles with hybrid or electric technologies, and introducing biofuel in aviation and haulage. In buildings, energy performance is expected to improve with the use of passive architecture, retrofitting of existing buildings and replacement of domestic fossil fuels use by electricity and renewable sources (Commission, 2015b),(Commission, 2015c).

Guided by the ETS, the EU cap-and-trade system is an important instrument currently available and feasible for GHG impact assessment, and therefore the DEESS associated externalities will use this system. Using the EU ETS will contribute to the development of a methodology that uses existing and available data within the energy sector.

3 Methodology proposal

The proposed methodology is outlined in six steps, as presented in Figure 3-1 (Gonçalves et al., 2015b). The objective is to combine the determination of the best location for the storage units with the definition of the best schedule of operation, giving the DM insights on his choice (and on the associated impacts of possible tradeoffs), as well as testing possible management schemes that may be proposed for a stationary DEESS within a smart grid environment.

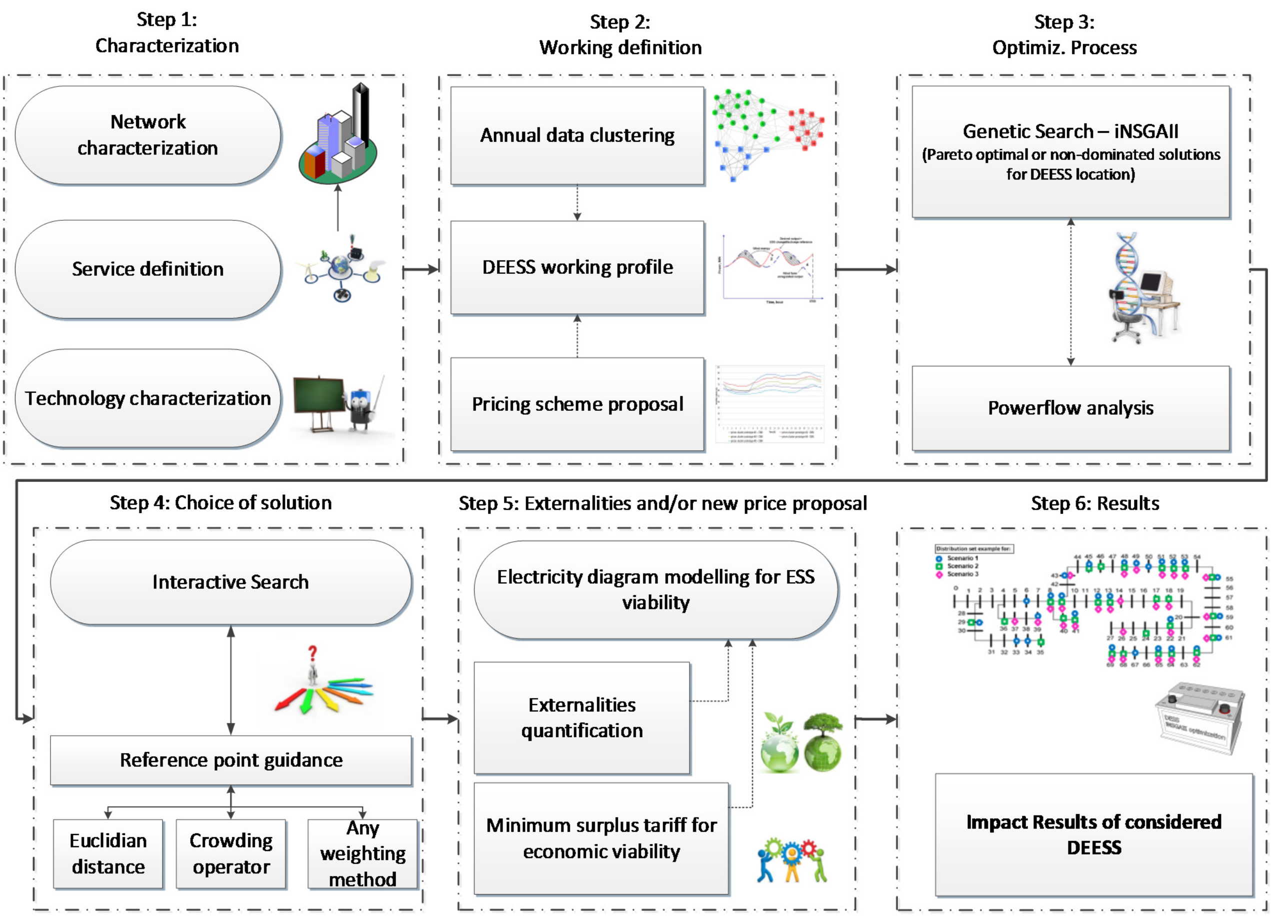


Figure 3-1 – Proposed methodology for DEESS assessment using iNSGA-II algorithm – Macro view

Each of the presented steps is further detailed in Figure 3-2. The methodology searches a Pareto front for one of possible scenarios, supported on data regarding the network, the storage technology and the defined service, from which the best possible set of DEESS locations will be chosen, as presented in Figure 3-2.

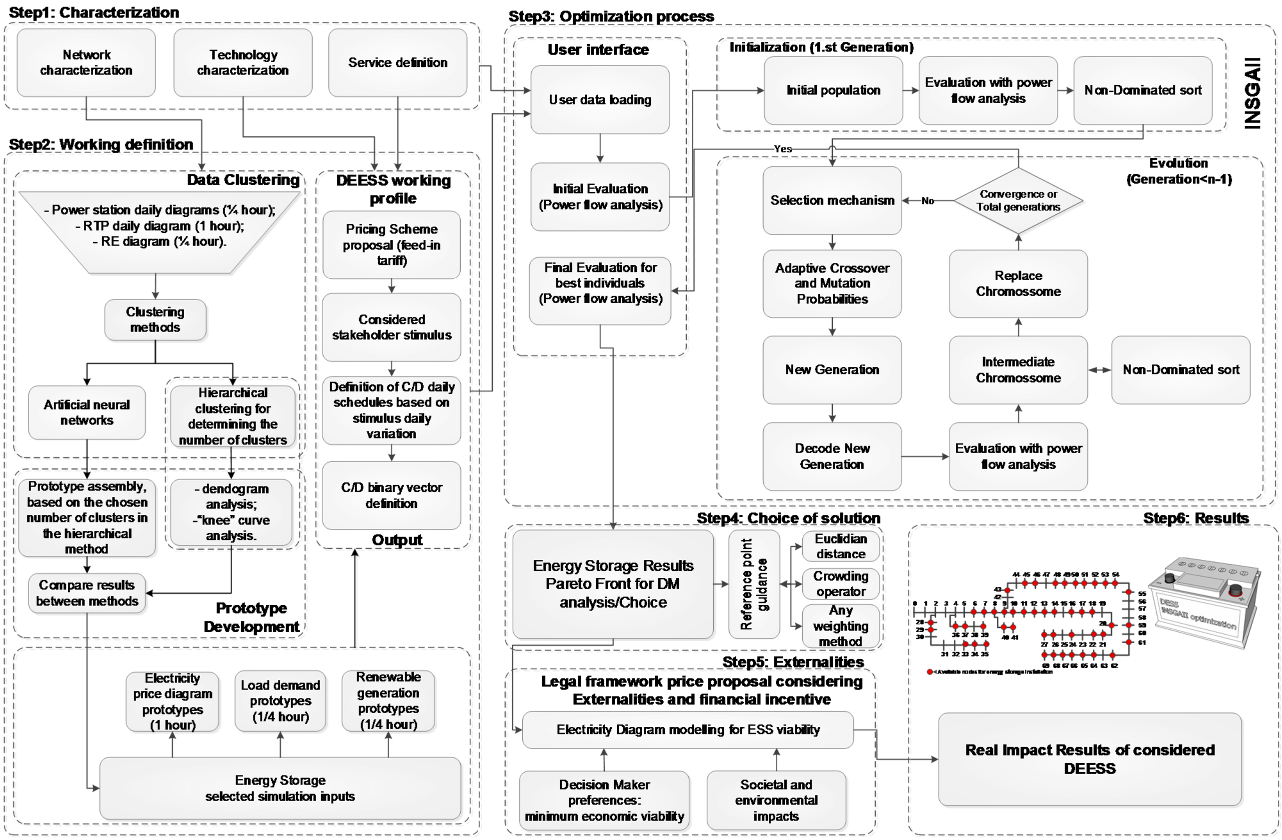


Figure 3-2 – Proposed methodology for DEESS assessment using iNSGAII algorithm – Detailed view

The *service definition* block is where the desired goal to be assessed is specified through management schemes. The proposed methodology is tested considering three plausible goals for ESS commonly highlighted in the literature and detailed in section 4.4.

The *technology characterization* block defines the technical characteristics of the considered ESS (battery plus power converter), since solutions depend on the considered technology and its working limits. This block provides information about the working periods for the definition of the management scheme (C/D profile) in the *DEESS working profile* block, also providing the capacity limits used in the optimization process, namely in the power flow analysis performed inside the genetic search (i.e the *iNSGAII* block).

The *network characterization* block defines the daily demand diagram of the distribution substation and the active and passive elements of the electricity grid. This step characterizes the entire network, describing buses, cables and interconnections. The information is compiled in data matrixes used to perform a power flow analysis with the help of the Matpower toolbox (Zimmerman et al., 2011) and Matlab™. Although the methodology is here applied to study the best ESS location within a distribution network (considering different management schemes), it may be applied to any type of grid, as long as the correct characterization is provided. The methodology does not consider potential problems arising in the operation of protection devices due to reversal of power flows.

The *Working definition* block, presented in Figure 3-2, includes the *Data clustering* and the *DEESS working profile* intermediate stage. In order to define a C/D profile for the storage elements and to evaluate the economic value of the operation, prototypes of daily LD profiles, as well as of energy market rates profiles and of renewable wind generation profiles, were needed. This work proposes a new method to obtain such profiles, using cluster analysis, namely through an artificial neural networks method, confirmed with a hierarchical clustering approach, included here in the *Data clustering* block. The *DEESS Working profile* block represents the second intermediate stage for the management scheme (MSch) definition of the considered ESS. Therefore, it combines the management goals of the DM, registered in the *Service definition* step, and the technical limits of the considered ESS.

The present work also implements a possible *pricing scheme* to be used for promoting DEESS exploitation, because the existence of a regulatory framework may stimulate the existence of market players intending to invest on energy storage. Since one of the main objectives is to balance the surplus/deficit periods of renewable energy (RE) availability, the energy recovered from energy storage is assumed to be rewarded on an equivalent basis to the energy that is displaced as explained in section 3.2.

The *iNSGAII* block uses the genetic algorithm presented in (Gonçalves et al., 2015a), to search for non-dominated solutions. The tool uses a “Binary Tournament Selection” based on the rank and crowding distance to choose the best individuals for the evolution process. An individual is selected if its rank is smaller than the rank of the other, or, if its crowding distance is greater than the crowding distance of the other in case they share the same rank. (Figure 2-9, section 2.3.3). For the considered case study, the iNSGAII population of possible solutions was assumed to be composed of 150 individuals for a maximum number of 100 generations (both values that were consistently above those needed for convergence to be attained).

The evaluation functions were integrated in the algorithm using powerflow analysis to assess the impact of each individual solution on the network performance.

The *Externalities* block represents the assessment of possible avoided greenhouse gas (GHG) emissions regarding the chosen solution (or set of chosen solutions), as well as a surplus tariff proposition that can improve the associated economic benefit. The new surplus tariff proposal is based on the solution's annualized cost and the annual economic benefit needed to obtain profit. After doing this economic analysis the DM will increase the perception of possible viable choices.

All the possible non-dominated solutions are presented in the Pareto optimal front as result of the optimization process. The final preferred solution must be chosen by the DM considering its own criteria, namely the tradeoffs between objectives. The stakeholders that can benefit from the developed methodology are the DSO, a private investor or any authority acting according to the societal interest.

3.1 Data clustering

The need for evaluating the DEESS contribution within a smart grid environment, presents an opportunity for data classification, considering the large data sets for dynamic grid analysis, such as the annual monitoring of distribution LD, energy market prices and wind power generation.

The following sub-sections present a methodology[5] to group information by similarity, enabling the analyses of the associated impacts on the electricity grid of the deployment of a DEESS, by providing reliable daily simulation profile prototypes of market price, LD and wind power generation (Miguel et al., 2016).

3.1.1 Clustering techniques

Cluster analysis is a convenient method for identifying homogenous groups of objects called clusters, aiming to group objects by similarity, but keeping a significant difference between them (Mooi & Sarstedt, 2010).

Clustering techniques could be divided in two main methods, namely the Partitional clustering and the Hierarchical clustering, as presented in Figure 3-3.

[5] This work was jointly developed with another PhD student.

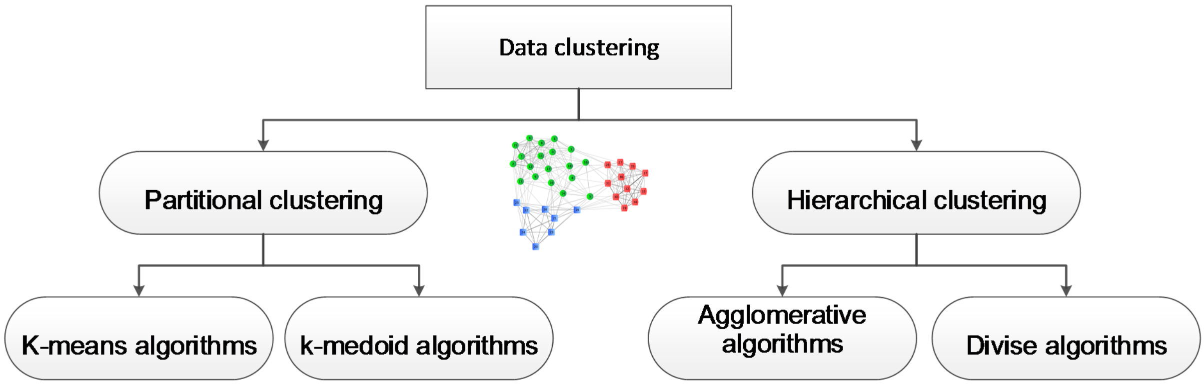


Figure 3-3 – Data clustering techniques

The Partitional clustering creates a partition of the database into a predefined number of clusters. In other words, it attempts to determine *k* partitions that optimize a certain criterion function. The Partitional clustering algorithms are divided in two main types; the K-means and K-medoid algorithms (Pujari et al., 2001).

The Partitional algorithms use an interactive optimization paradigm. It starts with an initial partition and by applying an interactive control strategy, it tries to swap objects to improve the quality of the clustering. The quality of the clusters will strongly depend of the initially selected partition. In the k-means algorithms a cluster is represented by its center of gravity while the K-medoid algorithms use the closest object from the center as the center representation.

The Hierarchical clustering methods create sequenced partitions, each one containing the previous one in a hierarchic way. There are two types of hierarchical methods, the agglomerative clustering algorithms and the divisive clustering algorithms.

The agglomerative clustering method starts with an equal number of clusters and objects (each cluster has only one object) that will be merged in pairs until the number of clusters reduces to *k* partitions. The merging procedure always considers the nearest pair of available clusters and terminates when the hierarchy of clusters is built with just a single cluster containing all objects (Pujari et al., 2001).

The divisive clustering method is an inverse process to the agglomerative clustering method, starting with all the records in one cluster and iterating to split each cluster into smaller groups.

An alternative method introduced by Teuvo Kohonen in the early1980’s, the self-organizing maps (SOM), is a type of artificial neural network (ANN) with an unsupervised learning process because the classes for the output vectors are not initially known (Kohonen, 1998). The Kohonen SOM could be compared to conventional clustering methods, considering the internal allocation rules and their performance (Sousa, 2006).

The cluster analysis used in the current methodology makes use of a hierarchical clustering method (HM) and an artificial neural networks method, more precisely the Kohonen SOM, as detailed in the following sub-sections. The final objective of the author is to develop cluster prototypes of daily price profiles, load demand profiles and wind generation profiles

3.1.2 Hierarchical Method (HM)

As previously mentioned, the hierarchical clustering method investigates possible groupings of data, by creating a structure similar to a hierarchical tree (Sousa, 2006). Such tree is comprised with a multiple level clusters hierarchy, where clusters at one level are grouped in clusters of a higher level. The adopted procedure to create the cluster profile prototypes is here only generally described, but a detailed description may be found in (Sousa, 2006).

First the input data are evaluated (in this case, market price diagrams, LD and wind power generation profiles), and the type of clustering results that are valuable to the analysis are identified. For the specific case, the assessment is based on either the magnitude of the difference between cluster members (defined as the difference between extreme values of a daily profile), or on the diagram shape.

The diagram shape comparison is performed by using the Euclidian distance between individual normalized vectors or/and intermediate vectors that represent the data clusters in the tree dendogram. Initially the assessment is performed between individual profiles but as a result of the data clustering, this comparison will be also performed between individual profiles and clusters or between clusters, until the hierarchical tree is composed of one final cluster.

The Euclidian distance between two profiles (x and y) is measured as shown in equation (15) considering 96 values of the profiles.

$$\|x - y\| = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_{96} - y_{96})^2} \tag{15}$$

The authors performed an analysis to the meaning of the obtained clusters by attempting to match with day types, namely weekdays, Saturdays, Sundays and holidays. After several tests, while for electricity profiles (LD and wind power generation) the most relevant was the shape of the profile, in the case of the price profiles, the magnitude of the difference assumed greater relevance to differentiate daily diagrams.

The sequence of partitions is assessed according to the distance between objects, namely their linkage distance that is characterized as single, complete, average, centroid or ward distance, the latter being used in the present case.

The following table presents the different ways to measure the linkage distance between objects, which is the main difference between existent clustering methods (Sousa, 2006).

Table 3-1 – Hierarchical clustering methods (Everitt et al., 2011)

Method	**Description**
Single linkage	Uses the minimum distance between objects under analysis. It tends to produce unbalanced and scattered clusters especially in large sets of data, without taking into account the structure of the formed clusters.
Complete linkage	Uses the maximum distance between objects under analysis. It tends to produce compact clusters with equal diameters not considering the structure of the formed clusters.
Average linkage	Uses the average distance between objects under analysis. It tends to group clusters with small variances. It could be seen as an intermediate method between *single* method and *complete* method. It considers the structure of clusters and reveals to be a relatively robust method.
Centroid linkage	Uses the distance between the clusters centroids or means. This method is one more averaging technique, assuming that the points can be represented in a Euclidean space for geometric interpretation.
Ward linkage	The distance between two clusters is the sum of squared deviations from points to centroids. The goal is to minimize the within-cluster sum of squares. Tends to produce clusters with a spherical shape and similar numbers of observations (representations), being also sensitive to outliers. It assumes that the points can be represented in Euclidean space, providing a geometric interpretation.

After calculating distances between objects it is possible to group profiles considering their proximity, using the shortest distance. The distance between clusters is determined each time a new cluster is created, comprising new objects or group of objects, until the hierarchical tree is composed of one single cluster. More detailed information regarding this procedure can be found in (Everitt et al., 2011).

3.1.3 Artificial Neural Networks (ANN) Method

The ANN method is based on the Kohonen SOM (Kohonen, 1998). This algorithm is able to capture eventual nonlinear statistical relationships between elements of data into a simple geometric relationship (neural network) on a low dimensional display, based on similarity and topology, a feature that is one of the most important advantages of the method.

Similar to the hierarchical method, this clustering method is also an example of unsupervised learning because the classes of the output vectors are not initially known. The used data in the training stage is crucial since the neural network is iteratively adapted in order to minimize a performance function, the result being an automatic mapping of the relationships between the inputs and outputs (Sousa, 2006).

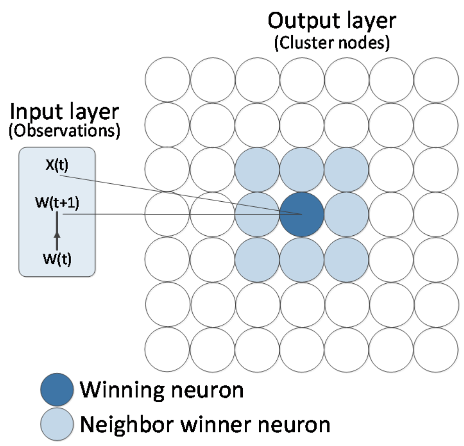


Figure 3-4 – Kohonen self-organizing map model (Everitt et al., 2011)

The neural networks contain two layers: an input layer of *x*-observations with a *p* dimension and an output layer representing *k* nodes for the *k* clusters, each one associated to a weight *w* with dimension equal to *p*. The clustering process occurs when an input vector is assigned to an output node characterized by a weight synaptic vector *w* with dimension equal to *p*.(Sousa, 2006). According to Everitt et al. (2011), the random weights initially assigned to nodes change with the learning (training) process, representing the allocation of input data to clusters. The stabilization of the iterative process eventually occurs when weights corresponding to cluster prototypes ensure that similar clusters are represented closely on the map (Sousa, 2006).

The ANN application was performed as shown in Figure 3-5 using the available MATLAB toolboxes.

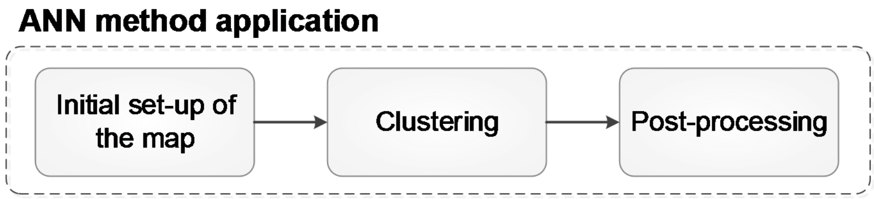


Figure 3-5 – ANN application for 2008 data clustering of LD, market prices and wind power generation

The *Initial set-up* block includes the annual input data (normalized for the load demand and wind generation) gathered in [96;366] matrixes, which represent the total days of 2008 on 0.25h samples.

The *Clustering* block is where data will be clustered based on similarity and topology, with a preference for assigning the same number of instances to each class. This step considered a total of 1000 training steps input space coverage, an initial neighborhood size of two, and a layer topology function that calculates neuron positions for layers whose neurons are arranged in an N dimensional grid (e.g. gridtop function). The N-dimensional neuron layer definition was guided by the hierarchical method results and using a layer distance function to find the distances between the layer's neurons given their positions. This step uses both the input data and the neuron layer network to cyclically adjust the weights associated with the input values. During the training phase, the network learns by adjusting the weights in order to be able to predict accurately the class label of input samples. Finally the input data are actually allocated/clustered according to the obtained weights in the neuron layer network.

The *post-processing* block just shows results in a graphical way, as examples in Figure 3-6 and Figure 3-7.

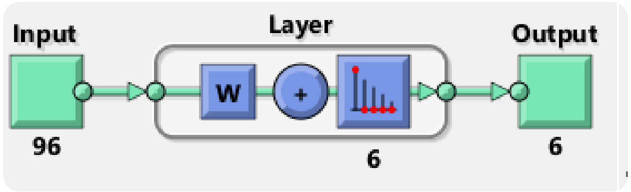


Figure 3-6 – ANN example for six clusters output

Figure 3-7 presents an example in which five of the six available clusters get almost all the hits (allocation of input diagrams).

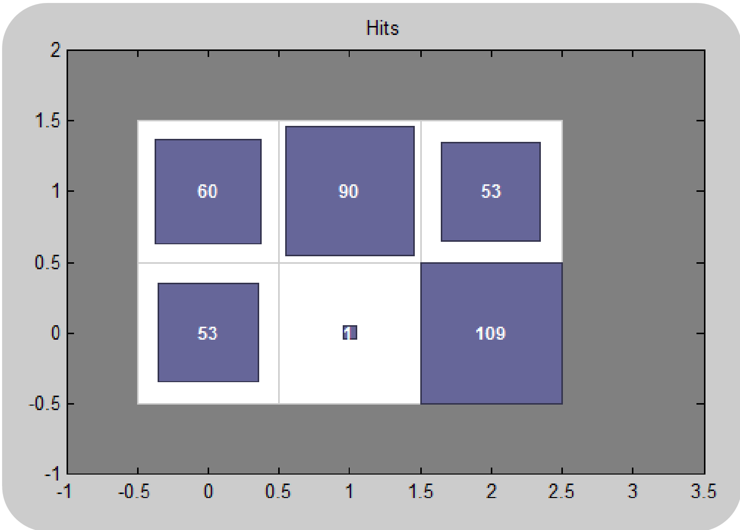


Figure 3-7 – Self-organizing map hits allocation example

3.1.4 Profile prototypes definition

The proposed clustering methodology, presented in Figure 3-8, was fed with one year of data on a quarter hour time step. The LD and wind power generation diagrams were obtained directly from the Portuguese electric energy sector databases. The electricity wholesale market prices for one year were converted from hourly data into quarter hour time step data.

In order to define the appropriate use of gathered data, an experimental setup was performed using two approaches for the data clustering techniques, one using the input data without any treatment and a second one where the input data were subjected to a normalization procedure such that the sum of all the elements of each vector equals 1, in order to cross-check their validity (Sousa, 2006).

The normalization process was performed using equation (16) where $Vector_i$ is the value of the ith element of the vector to be normalized and m is the number of elements (m=96).

$$Normalized\ vector_i = \frac{Vector_i}{\sum_{i=1}^{m} Vector_i} \quad (16)$$

This experiment showed that in the case of the electricity profiles, the use of the shape of the diagram resulted in data being differentiated in workdays and weekends. However, in the case of the market price diagrams, the magnitude similarity between diagrams resulted in more discrimination than when using the shape of the diagram. An important issue was the need to adjust the data to the two clock changes of the daylight savings scheme, namely on the last Sunday of March and October.

The hierarchical method helped to choose the appropriate number of clusters graphically, using the tree dendogram and the inflexion point of the curve that relates the distances between clusters with the number of clusters (cf section 4.1 related to the case study example) (Salvador & Chan, 2004). A comparison was made between the output of both methods regarding the assignment of day types (working day, Saturday, Sunday and holiday) to clusters.

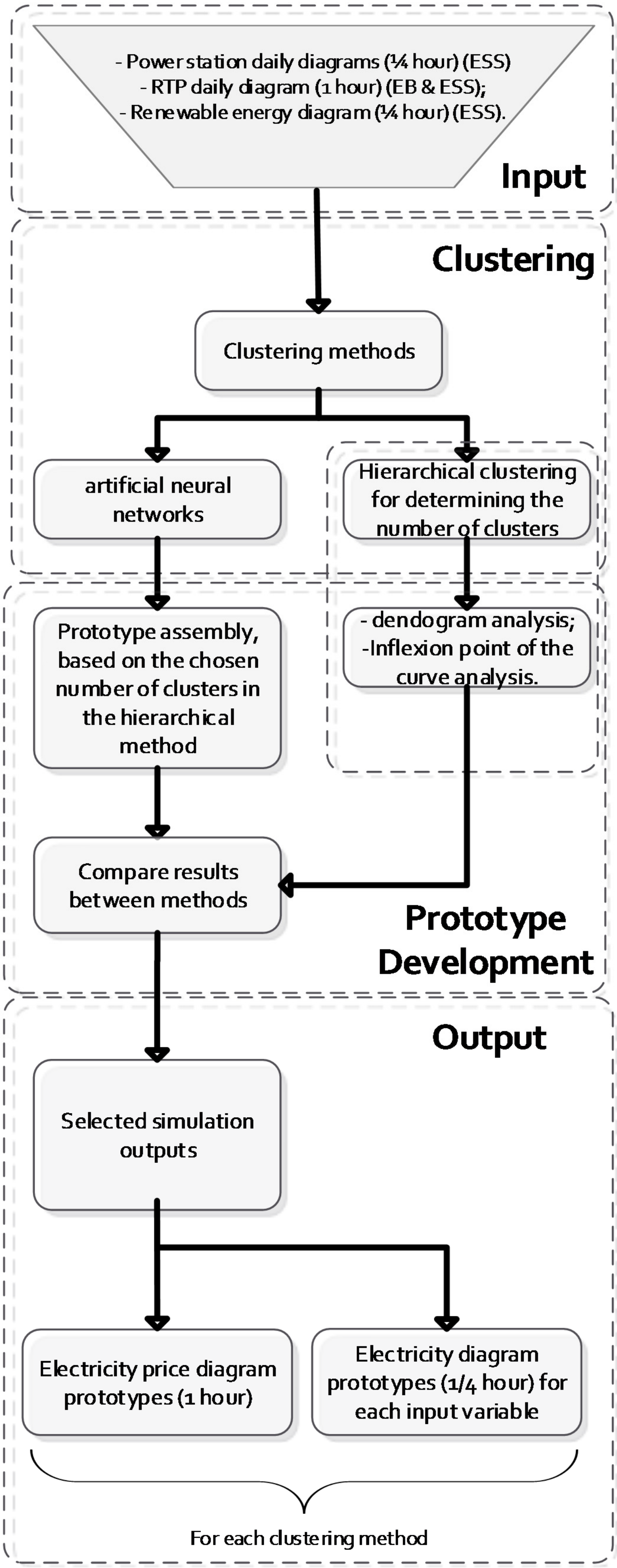


Figure 3-8 - Methodology for profile cluster prototypes of price, electricity consumption and wind power generation (Miguel et al., 2016).

The output of this method provides one profile prototype for each cluster in each clustering technique. The profile prototype of each cluster was obtained with an average of the profiles allocated to it.

These profile prototypes, and their weight in terms of the number of days per year in which they apply, are then important tools for building different scenarios useful for studies that evaluate the deployment of new technologies, such as the use of distributed electric energy storage (Gonçalves et al., 2013) or residential energy management systems (Miguel et al., 2013).

3.2 Proposal of a pricing scheme for the energy storage service

Since the research aims to contribute to the integration of electric ESS within a radial distribution system (RDS), a definition of the regulatory framework for the management of the infrastructure is required.

Being the purpose of promoting ESS the benefits these systems could bring to maximize the generation of electricity from renewable sources, it seems plausible to consider electric ESS on an equivalent basis to a renewable generator, or what in Portugal is defined as a Special Regime Producer (SRP). In fact, a better match between supply availability and demand needs is expected to help maximizing the interest on investing in renewable generation. However, this feature is not yet accounted for in the current legislation.

Table 2 – SRP characterization according to the production process(ERSE, 2009)

Electricity generation based on :
a) Water resources for power up to 10 MVA and in some cases up to 30 MW;
b) Using other sources of renewable energy;
c) Based on waste (municipal, industrial and agricultural);
d) At low voltage, with installed capacity limited to 150 kW;
e) For micro, with installed power up to 5.75 kW;
f) Through a process of cogeneration.

The Portuguese last resort retailer is obliged to purchase all energy produced by the SRP, with administratively defined prices (net-billing tariff), or resulting from a bidding process upper bounded by values previously set by the government based on the avoided costs of investment in new facilities, as well as the avoided costs of energy (fuel costs) and environmental impacts (avoided GHG emissions cost). The final reward to the producer depends on delivery periods, generation diagram shape and primary energy source (MIBEL' council of regulators, 2011).

The last resort retailer, when making purchase offers on the Iberian electricity market (MIBEL), takes into account the energy acquired in the special regime. Hence, the special regime production does not appear explicitly in the energy market, but it has influence on the price since it influences the volume of the purchase offers.

Figure 3-9 presents the evolution of the average prices from 2000 to 2012, including the regulated market and the SRP market (ERSE, 2013).

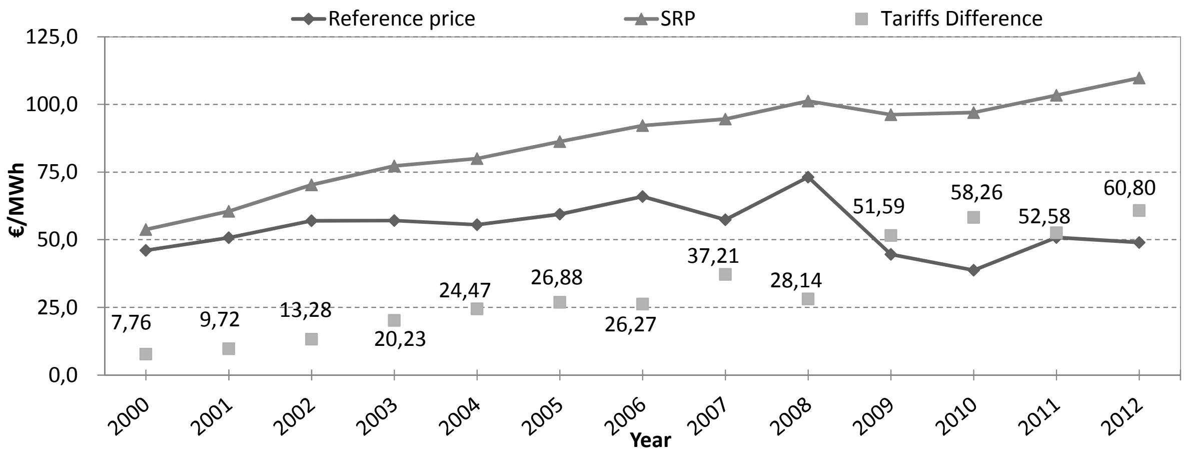


Figure 3-9 – Average annual cost between PRE and regulated market (ERSE, 2013)

The proposed pricing scheme should consider the electric ESS as a SRP that buys energy at the daily market price and sells it at SRP prices, in high demand periods. As DEESS may play an important role to support the increased share of RE, avoiding the use of backup thermal generation, it is admissible to consider that the DEESS service is priced accordingly, as if they were SRP. In this study, an average SRP surplus tariff of 24.18€/MWh (referring to 2008) was used. It was the current value in 2008, for which consumption data were available.

3.3 Optimization method

The following sections detail the approach briefly described in section 2.3, namely the population definition, the crossover method, the coding and decoding technique, termination operator and the adopted objective functions to measure the DEESS network impacts of each solution.

3.3.1 Initial population generation

The initial population is randomly generated considering a predefined number of individuals (Nind) with a vector of length equal to the total available nodes predefined by the user. Moreover, during the random generation, it is assured that the individuals of a certain population are all different in order to guarantee a high genetic diversity and to avoid repeated computation. Therefore, it should be guaranteed that the total number of individuals for each population are less than the possible combination of available nodes (expression (17)).

$$Nind \leq 2^{nnos} \tag{17}$$

With

$Nind$ – The total number of individual in each generation;

$nnos$ – The total number of available nodes for ESS installation.

3.3.2 Multi-point crossover

Since the coding technique is based on a binary assignment of the entire buses of the network, the chromosome tends to become very long. For that reason, and ambitioning the best performance of the algorithm, the author uses a multi-point crossover.

On the chosen multi-point crossover, the cutting point divide the chromossome in 2 bit parts, leaving a last part of 3 bit for odd chromosome lengths.

Parent 1	1	1	0	1	0	0	1	1	0
Parent 2	0	0	1	1	0	1	1	1	0
Descendent	1	1	1	1	0	1	1	1	0

Figure 3-10 - Example of the Multi-point crossover technique.

The proposed method allows a fast crossover over the wide length chromosomes, as well as maintaining the descendants inherit characteristics from both parents according to a defined probability (pc).

3.3.3 Coding and Decoding Technique

The definition of the available nodes for the installation of storage units is made by the DM, based on technical criteria (e.g. which buses have critical load factors). The DM can easily define the availability of a specific node for ESS installation using a binary number (1 or 0). This technique will create a matrix of chromosomes with total length equal to the predefined number of individuals (Nind), as presented in Table 3-3. Each chromosome has a number of bits equal to the number of available nodes (nnos) for ESS installation.

Table 3-3 – Coding technique for available buses identification

Node number	1	2	3	4	…	n-1	N
Availability Status	0	1	1	0	…	1	0

The correspondence between the nodes in the network and the chromosome element is achieved through the use of a reference vector with the same size of a chromosome, as depicted in Table 3-4.

The use of a reference vector (as presented in Table 3-4) will enable the use of shorter length chromosomes because it will assure the generation of valid individuals. After the creation of each population, the network model must be updated with the availability of storage.

Table 3-4 – Available chromosomes' matrix

	Node number for gene position			
Reference Vector	2	3	…	z

3.3.4 Termination

Genetic algorithms are stochastic search tools and for that reason it is difficult to specify convergence criteria. However, improved NSGA-II uses as a first termination criterion the maximum number of generations (Npop), and secondly a specified convergence threshold (Cth). The motivation for using the diversity of population lies in the fact that the individuals of generation "R_{t+1}" may have similar performance to generation "R_t" implying a progressive reduction of genetic diversity. If the diversity of population does not suffer any changes, we may assume that GA converged. Figure 3-11 shows the convergence after 105th generation by using the genetic diversity operator (Gdiv) along 15 generation threshold (Cth).

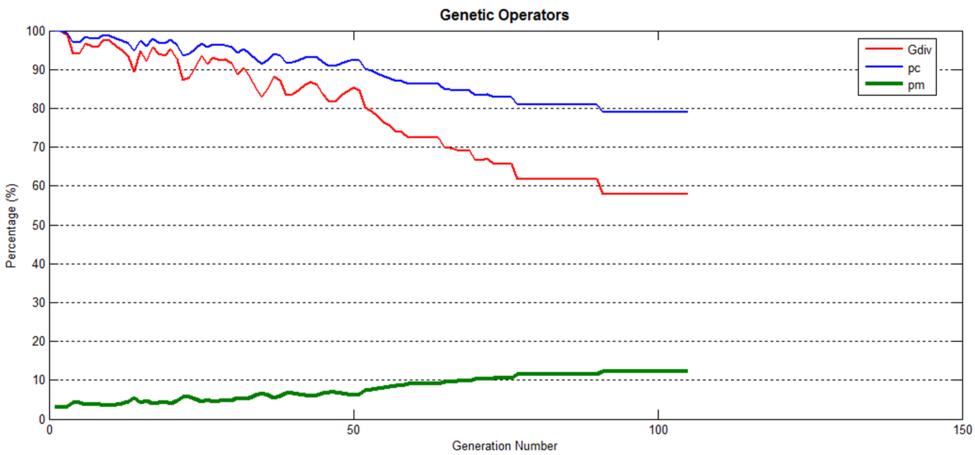


Figure 3-11 – Evolution of improved NSGA-II using a termination criteria

3.3.5 Objective functions

Considering a 24h time horizon, the assessment of the best locations for DEESS consists in the identification of the best buses where installed storage units will minimize network energy losses (NEL), network voltage quadratic mean deviation (NVqmd) and the network storage annualized cost (NSAC), while maximizing the benefit associated with the daily purchase and sale of energy in different time periods, hereinafter designated as network energy rate benefit (NERB).

3.3.5.1 Network Energy Losses (NEL)

The NEL objective function to be minimized, described in equation (18), is the sum of the network power losses (PL) in all the *n* branches of the medium voltage (MV) distribution network during the whole day. The elementary time interval is a quarter-hour (t_j=0.25h) so the data set has 96 values (m=96).

$$\mathrm{NEL} = \sum_{\mathrm{i}=1}^{\mathrm{n}} \sum_{\mathrm{j}=1}^{\mathrm{m}} \frac{\mathrm{PL_{ij}}}{\mathrm{t_j}} \tag{18}$$

3.3.5.2 Network Voltage Quadratic Mean Deviation (NVqmd)

The NVqmd objective function to be minimized, described in equation (19), is the maximum daily network voltage quadratic mean deviation (NVqmd) for all individual voltage deviations (VD) in the *N* network buses, relative to the voltage reference value (V_{ref}).

$$NVqmd = Max_{i=1..m\ time\ steps;} \sqrt{\frac{\sum_{k=1}^{N} {VD_k}^2{}_i}{N}} \tag{19}$$

3.3.5.3 Network Storage Annualized Cost (NSAC)

The third objective function, to be minimized, is the network storage annualized cost (NSAC) for installing *x* units of DEES with an individual capital cost (C_{ac}), as presented in equation (20).

$$\mathrm{NSAC} = x \times C_{ac} \tag{20}$$

The C_{ac} is calculated considering the capital costs (c_c) and the capital recovery factor (CRF) as presented in equation (21). Where d is the dimensionless discount rate and y the expected life of the equipment, measured in years;

$$C_{ac} = c_c CRF = c_c \frac{d(1+d)^y}{(1+d)^y - 1} \tag{21}$$

3.3.5.4 Network Energy rate benefit (NERB)

The fourth objective function, to be maximized, is the network energy rate benefit (NERB) considering the energy tariff (C) and the required energy (E) for charge(ch) and discharge(dch) periods during the 96 elementary time intervals, as presented in equation (22).

$$NERB = \sum_{j=1}^{m} (E_{dch} \times C_{dch} - E_{ch} \times C_{ch})_j \tag{22}$$

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4 Case study

In order to test it, the methodology was applied to a case study. Due to the lack of detailed data with enough quality, the network characterization of the physical infrastructure was based on a standard IEEE network. All data used in the optimization process was based on the Portuguese energy market, and treated using clustering methods according to the previously developed clustering methodology.

4.1 Data clustering process

The first step to define the appropriate number of clusters was the analysis of the dendogram or tree of clusters that resulted from the clustering process. (cf. in section 3.1). Figure 4-1 and Figure 4-2 illustrate an example of a tree dendogram and the representation of the relationship between the obtained number of clusters and the distances between the centers of clusters. Using both figures the selection of the number of clusters can be more accurately justified as the single use of any of them results in a degree of uncertainty, the threshold in the case of the dendogram, as depicted in Figure 4-1, and the location of the inflexion point of the curve, as observed in Figure 4-2. This technique was applied to select a set of plausible scenarios, and a total of 5 clusters were selected in all cases.

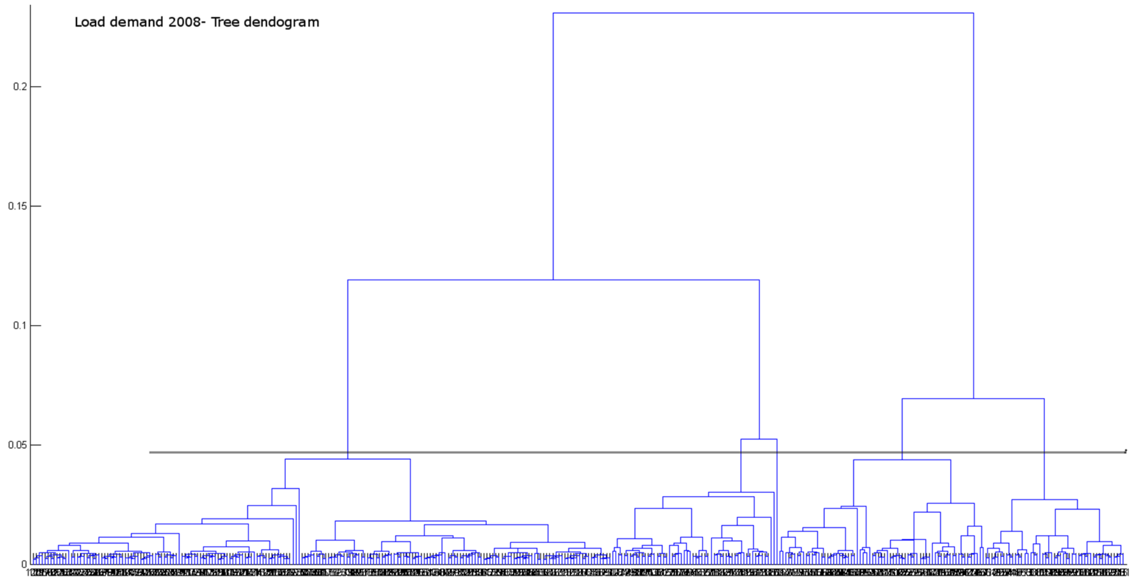

Figure 4-1 – Tree dendogram representing the clustering of LD daily profiles for 2008

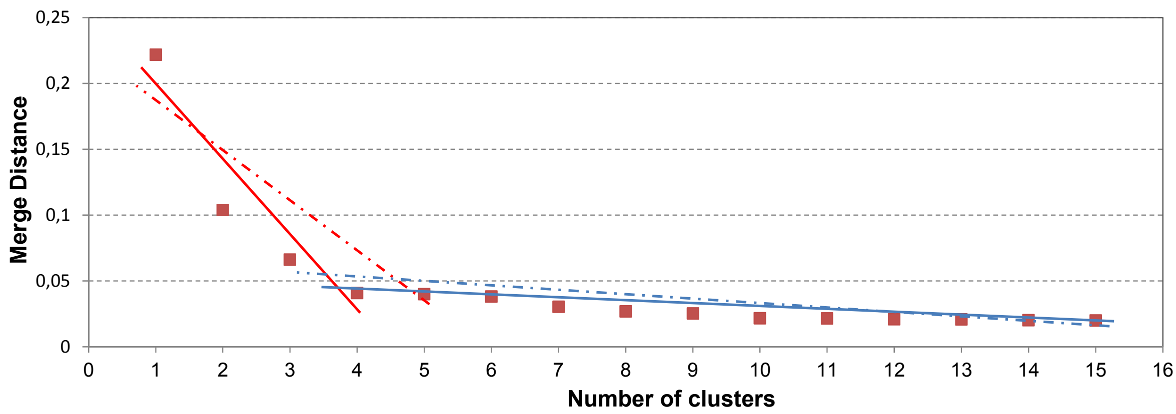

Figure 4-2 – The relation of the distance between clusters with the number of clusters for the LD in 2008.

4.1.1 Clustering of wholesale market price profiles

In order to compare the data allocation, verify the similarity of results with both methods, and understand the meaning of the clusters, the obtained outputs were analyzed in terms of the total number of allocated days (hits), on weekdays, weekends and holidays. As an example, Table 4-1 and Table 4-2 provide the comparison of electricity price profiles. The resulting clusters for the electricity prices did not show a particular correspondence to the type of day, no cluster being formed more with a type than with other. Although the current market situation creates conditions for this to happen, it suggests also that the natural consumption variation between workdays and weekends is not influencing prices.

Table 4-1 – Data allocation for 2008 electricity prices performed with the hierarchical method.

5 CLUSTER'S ANALYSIS – HIERACHICAL METHOD					
Cluster N.º	**Total hits**	**Week days**	**Saturdays**	**Sundays**	**Holidays**
1	42	35	3	2	2
2	71	27	20	22	2
3	93	81	9	3	0
4	44	44	0	0	0
5	116	64	20	25	7
Total	**366**	**251**	**52**	**52**	**11**

Table 4-2 – Data allocation for 2008 electricity prices performed with the artificial neural networks method

5 CLUSTER'S ANALYSIS – ARTIFICIAL NEURAL NETWORKS					
Cluster N.º	**Total hits**	**Week days**	**Saturdays**	**Sundays**	**Holidays**
1	36	36	0	0	0
2	101	84	9	8	0
3	108	63	24	17	4
4	69	49	9	8	3
5	52	19	10	19	4
Total	**366**	**251**	**52**	**52**	**11**

The resulting clustering price prototypes can be visualized in Figure 4-3. Both methods present similar types of price prototypes and the approximate same number of hits. This resemblance ensures that any of the clustering methods may be used for generating reliable simulation prototypes.

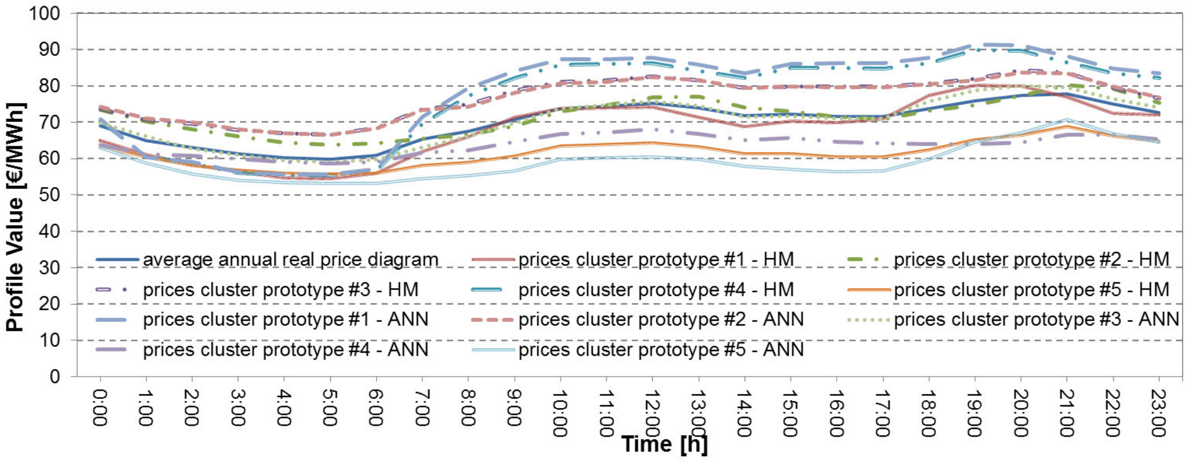

Figure 4-3 – Price prototype clusters for the HM and the ANN method, for 2008.

The prototypes show that ANN cluster#1 and HM cluster #4 are similar, the first one based on the ANN method and the second on the HM method. These two clusters present the largest variation between maximum and minimum daily market prices. The minimum and maximum obtained values for ANN method cluster #1 were 55.47 €/MWh and 89.86 €/MWh, and for HM cluster #4 were 55.66 €/MWh and 91.32 €/MWh.

Figure 4-4 presents the prototypes price range. Considering the average price, the maximum variation above the average profile was 15.37 € and below that profile was 15.18 €. The results show a small variation range in the prototypes values.

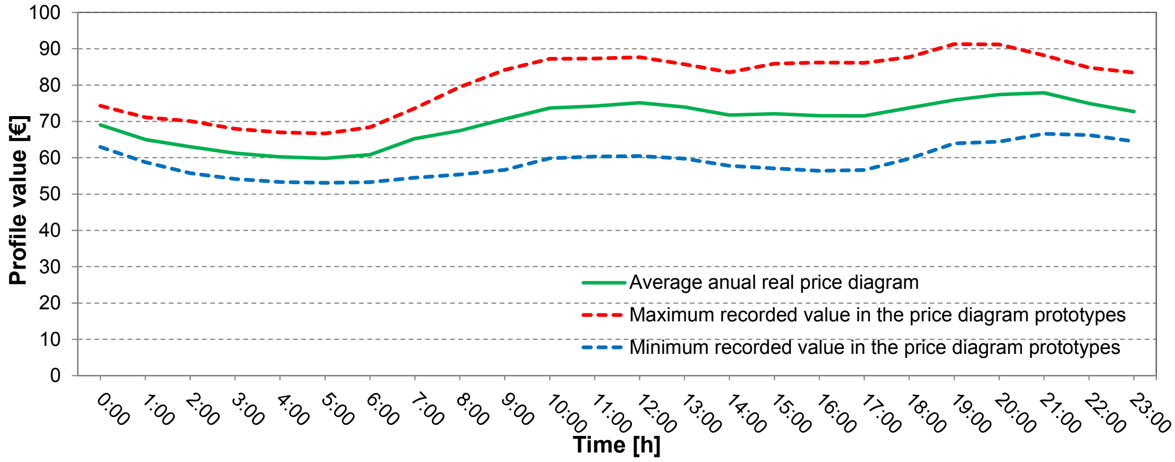

Figure 4-4 – Prototypes price range variation, for 2008.

If the stimulus to use storage consists in economic incentives based on market price diagrams, the viability of investments in storage might be dependent of technology development to increase total system efficiency. Since technology improvements are costly, the stimulus to investors may require a feed-in tariff scheme, such as the one proposed in section 3.2.

4.1.2 Clustering of LD profiles

Both methods presented rather segmented clusters in the electricity demand profiles (based on weekdays and weekends). The differences between methods were essentially related to the total number of allocated days. For different distributions, another measurement method may be used (e.g. complete linkage). The holidays were not represented in any particular cluster, most likely because these days normally present patterns similar to weekends. The results for both methods, regarding the 2008 high voltage (HV) LD are presented in Table 4-3 and Table 4-4.

Table 4-3 – Data allocation for 2008 HV LD performed with the hierarchical method.

5 CLUSTER'S ANALYSIS – HIERACHICAL METHOD					
Cluster N.º	**Total hits**	**Week days**	**Saturdays**	**Sundays**	**Holidays**
1	24	1	2	17	4
2	53	0	18	33	2
3	37	0	32	0	5
4	55	55	0	0	0
5	197	195	0	2	0
Total	**366**	**251**	**52**	**52**	**11**

Table 4-4 – Data allocation for 2008 HV LD performed with the artificial neural networks method.

5 CLUSTER'S ANALYSIS – ARTIFICIAL NEURAL NETWORKS					
Cluster N.º	**Total hits**	**Week days**	**Saturdays**	**Sundays**	**Holidays**
1	52	1	43	3	5
2	61	0	8	47	6
3	92	92	0	0	0
4	108	105	1	2	0
5	53	53	0	0	0
Total	**366**	**251**	**52**	**52**	**11**

In order to develop a prototype, the clustered data were used to obtain an average profile of each cluster. The developed prototypes for each method are presented in Figure 4-5 and Figure 4-6. The prototypes are similar for both methods, which is likely explained by the well-defined pattern of energy consumption, even considering the mix of industrial and residential consumers.

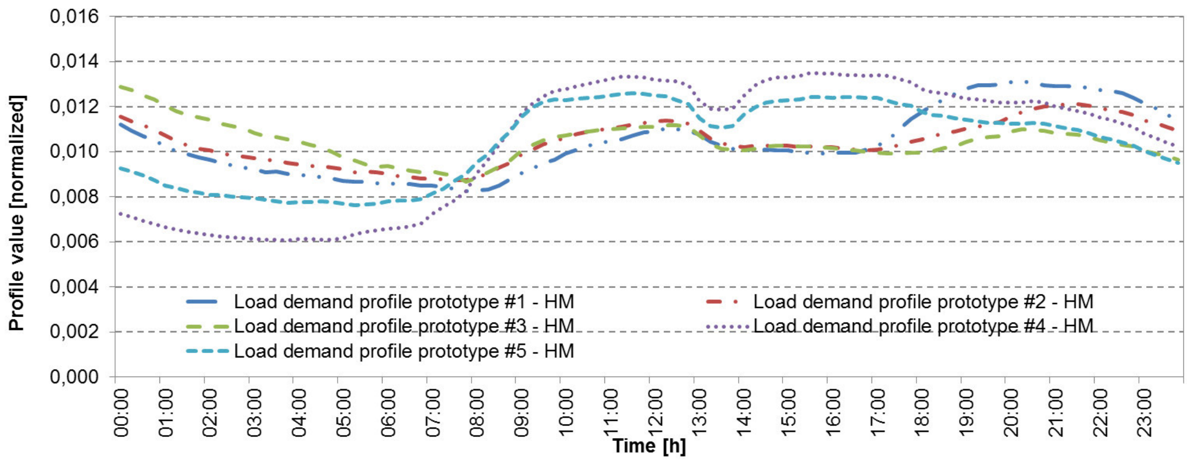

Figure 4-5 – HM 2008 cluster prototypes for HV LD.

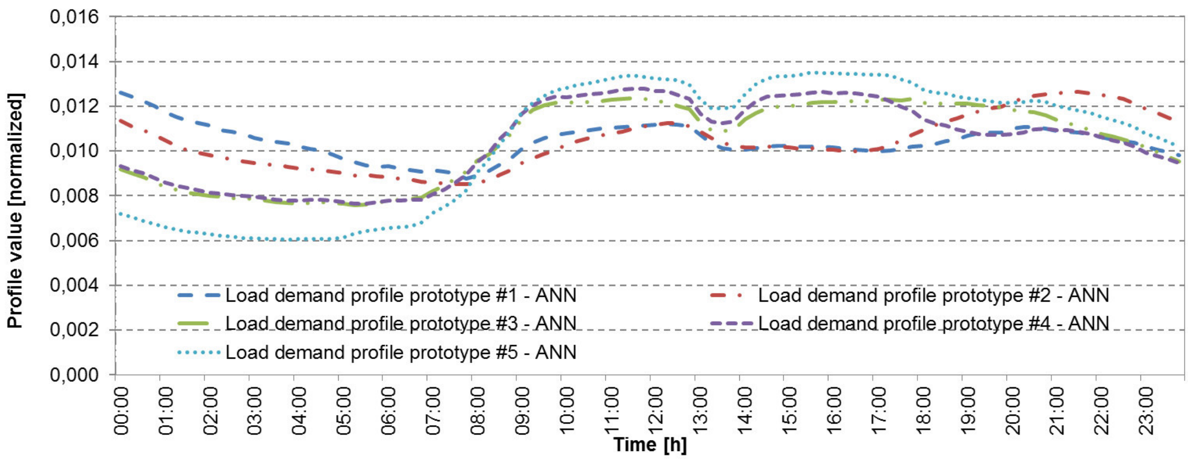

Figure 4-6 – ANN method 2008 cluster prototypes for HV LD.

In order to determine the profile variation range, the average profile for all data was compared to all five obtained prototypes. This process allowed to obtain the average variation range of the profiles, as presented in Figure 4-7 and Figure 4-8. Taking into consideration the differences between extreme values, and based on one year of data, Figure 4-7 suggests that the average profile may be used as a benchmark reference for demand response studies.

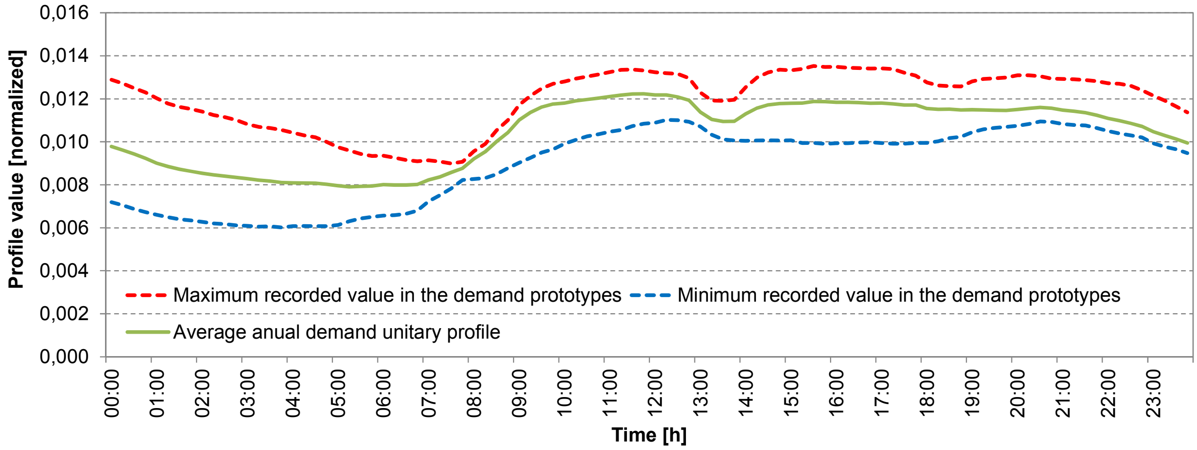

Figure 4-7 – Representation of the variation range of HV LD cluster profiles for 2008.

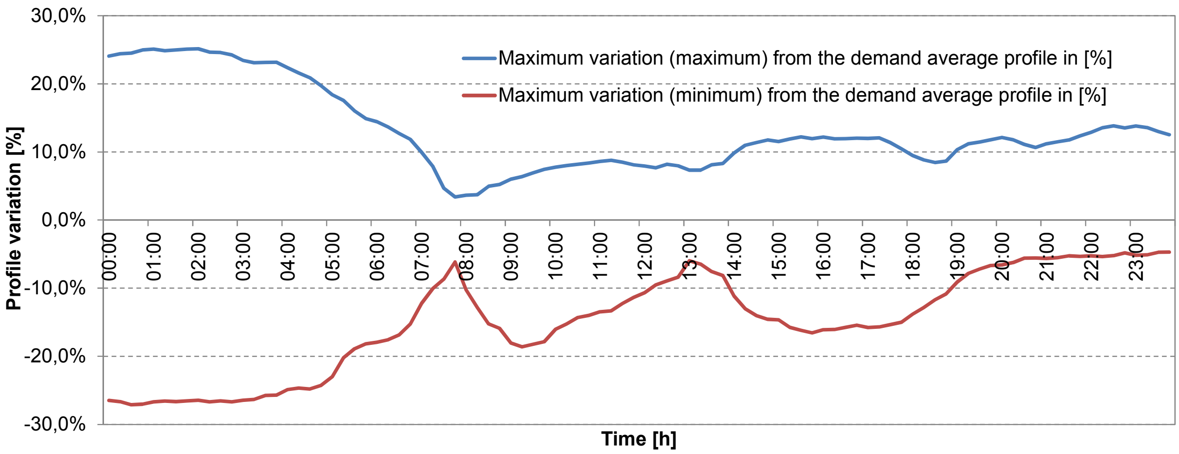

Figure 4-8 – Extreme variation of HV LD cluster profiles around the average, for 2008.

4.1.3 Clustering of wind generation profiles

As one of the major motivations for storage is to increase the potential of renewable energy by decoupling the periods of usage from the periods of generation, the clustering of historical data from renewable energy generation allows the analysis of different daily patterns and provides insight on their relevance. The obtained prototypes were dissimilar as expected, due to the unpredictability of this energy source, as shown in Figure 4-9. The difference between maximum and minimum values in Figure 4-9 shows that a single average profile is of limited use. ANN cluster #1 (17.21%) and ANN cluster #5 (13.11%), representing 30.33% of the wind pattern profiles in one year time, show clearly the relevance of the integration of energy storage systems. On ANN cluster #1, the energy generated from 00:00 to 08:00 can eventually be stored to be used in periods of higher consumption, while in cluster #5, the interest in storage is not so obvious, as the maximum generation occur in periods when consumption is traditionally high.

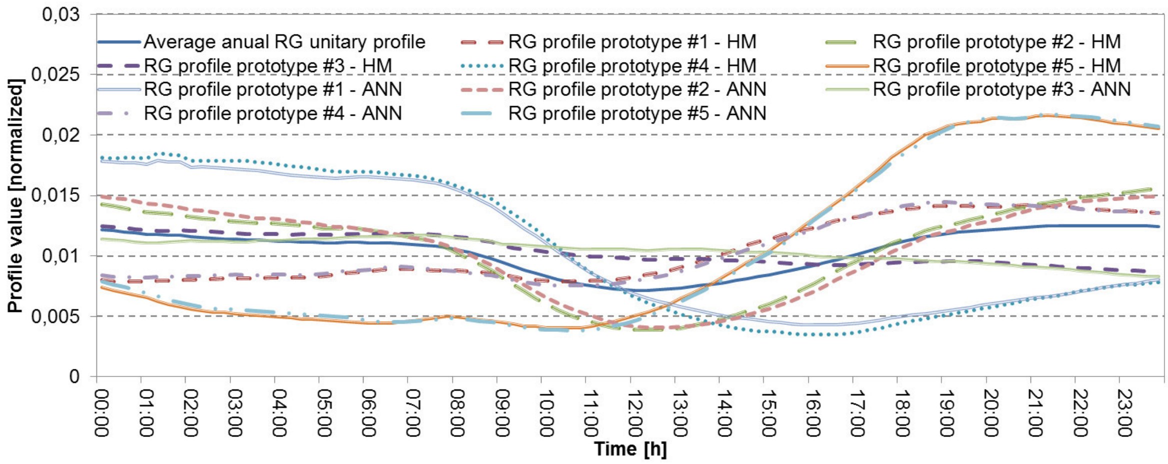

Figure 4-9 – Renewable HM and ANN prototypes for the year of 2008.

Figure 4-9 shows the significant variation in wind generation prototypes which can leverage the use of ESS. Potential scenarios can be drawn when combining prototypes as shown in Figure 4-10, however their representativeness will not guarantee the plausibility of scenarios in real conditions.

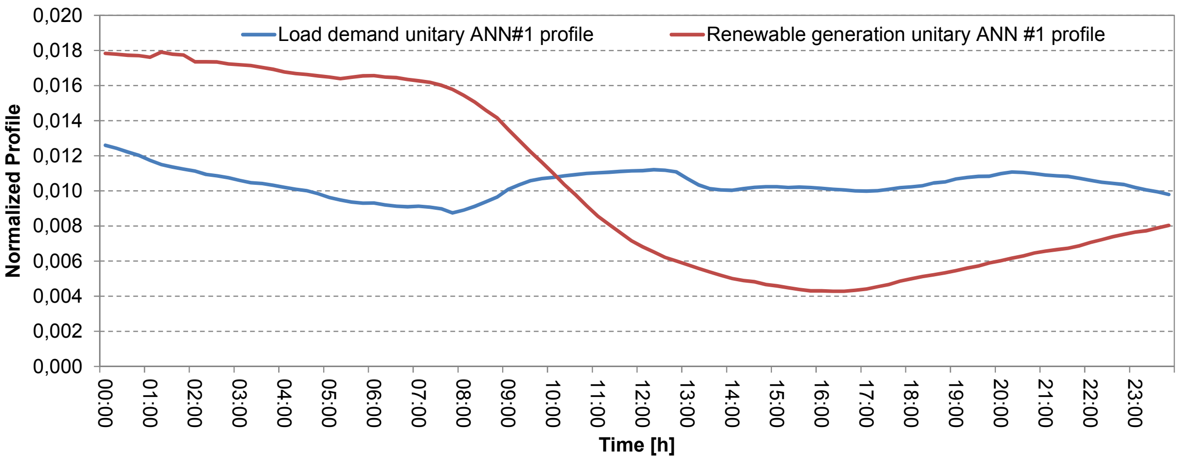

Figure 4-10 – Clusters #1 for HV LD and renewable energy generation.

In fact, cluster #1 of the renewable generation and cluster #1 of LD (which represent 17.21% and 14.21% of the number of occurrences in one year, respectively) show situations of particular interest of energy storage to maximize the benefits of renewable energy due to the visible decoupling between generation and consumption.

Table 4-5 presents the annual representativeness of the obtained prototypes using the ANN method.

Table 4-5 – Prototypes annual representativeness

Prototype n.º	Daily price profile [%]	Prototype n.º	HV LD profile [%]	Prototype n.º	RE generation profile [%]
1	9.84%	1	14.21%	1	17.21%
2	27.60%	2	16.67%	2	22.13%
3	29.51%	3	25.14%	3	26.50%
4	18.85%	4	29.51%	4	21.04%
5	14.21%	5	14.48%	5	13.11%
Total	100.00%	**Total**	100.00%	**Total**	100.00%

4.2 Technology characterization

The data used to perform the simulation of storage systems was obtained from a manufacturer regarding a nanophosphate lithium ion battery with the respective power converter (Systems, 2013), (Vartanian, 2010), (Systems, 2012).

According to these data, a total energy of 61.13Wh/cell was assumed, corresponding to 95% of depth-of-discharge. This option was based on the manufacturer information indicating more than 7000 cycles even with 100% depth-of-discharge (Systems, 2013).

Given the individual cell dimensions of 7.25x160x227mm (Systems, 2012), the proposed solution required roughly 0.1m^3 for the battery systems (a battery pack of two Rows of 180 cells, with a total capacity of 22 008 Wh) without power converter, a volume which could be easily integrated in any power transformer facility.

According to several manufacturers, a plausible 90% efficiency can be expected for the power converter (NEC, 2013) when performing a complete charge/discharge cycle, assuming a nominal discharging capacity of 20.85 kW and requiring a charging power of 23.17kW per power transformer.

The author considered three different ways to obtain the unitary DEESS system cost, considering different sources of data.

The first source of data (J. Vasconcelos et al., 2012), presented in Table 2-8 of section 2.1.4, supply unitary costs of 300€/kW for the PC and 450€/kWh for the storage system, resulting in a total estimated capital cost of 17 374.50€ for the specified capacity.

The second source of data, a website from a manufacturer (BuyA123baterries, 2014), supplied a unitary cell price of 51.70€, the total storage system capital cost amounting to 6 949.80€ for the estimated 360 cells. The PC price used the same data as in the previous paragraph. The total estimated capital cost amounts to 25 561.80€.

John, J. St. (John, 2014), representing a third source of data, presents a maximum of 1 200USD/kW for an hour of storage for AC systems, giving an estimate of 44.31€ for each unitary cell, amounting to a total capital cost of 22 902.77€

Using equation (4) and (5) presented in section 2.1.4, the author obtained the annualized capital costs presented in Table 4-6.

Table 4-6 – Summary costs table for the considered unitary storage solution

Option n.º	Calculated annualized capital cost [€]	Unitary capacity cost [€/kW]
1	2 029.85 €	87.62 €
2	2 986.37 €	128.91 €
3	2 675.72 €	115.50 €

The author considered, conservatively the highest obtained value of 2 986.37 €, corresponding to option 2.

4.3 Network characterization

As an example of a distribution network, the case study network was based on the IEEE 69 bus, 12.66kV RDS (Sahoo & Prasad, 2006), a frequently used test network (R.M. Vitorino et al., 2013), (Romeu M Vitorino et al., 2009), (Mora, 2012). The network includes an 8 MVA substation and 69 nodes, 48 being load-points (distribution transformers) with a total power of 4.66MVA (peak period) of which 3.8 MW is active power and 2.69 MVAr is reactive power. The network in its radial configuration had all the boundary tie-switches in the open position.

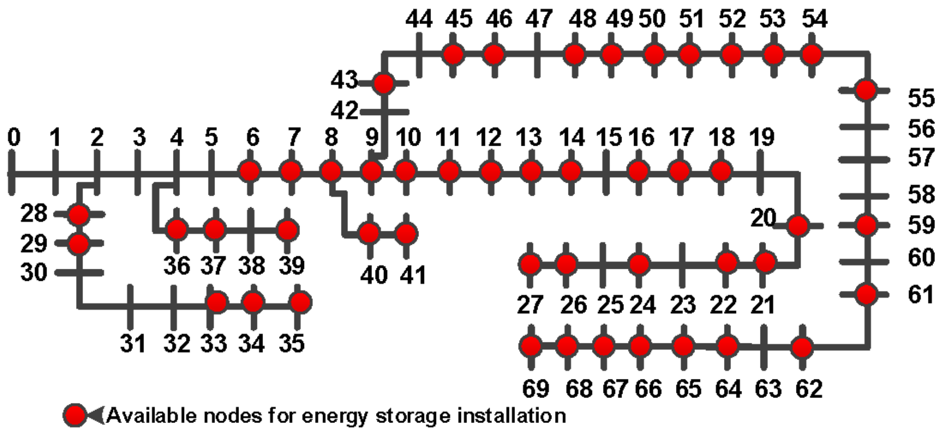

Figure 4-11 - 12.66kV radial distribution systems (Mora, 2012)

As shown in Figure 4-11, the RDS included 48 distribution transformers which the DM may consider as possible locations for the ESS units, depending, among other factors, on the availability of physical space.

To test the methodology, data from different sources regarding the Portuguese market were used. The information regarding market prices was extracted from “The Iberian Energy Derivatives Market Exchange or MIBEL” website. EDP Distribuição (the Portuguese DSO) provided the distribution LD data, derived from an annual measurement at the Pinheiros substation located in the city of Leiria in Portugal. The wind power generation data was extracted from the information center website of the Portuguese Transmission System Operator (TSO).

4.4 ESS working profiles

The energy storage charging and discharging daily behavior can be very diverse depending on the DM preferences. Based on the literature review, plausible DM goals were considered, according to three possible management schemes:

1. Management scheme A – To maximize profit from daily energy spot market rates;
2. Management scheme B – To minimize daily energy distribution network losses;
3. Management scheme C – To maximize the societal value of wind generation.

Considering the three previous stimuli, the author proceeded to the definition of a C/D binary vector. The five prototypes obtained at the clustering stage for energy market rates, distribution network LD and wind generation were used for the charging/discharging profile definition.

In order to increase the C/D daily periods the author considered, as a general approach, for management schemes A and B, the use of the average value of each daily data set as a reference. The storage units should charge and discharge when the daily profile presents the extreme values below and above the reference value, respectively. The designation of "-1", "1" and "0" was adopted, to define if the storage system is charging, discharging or on standby mode, respectively.

Figure 4-12 shows the market prices variation considering the developed prototype 5.

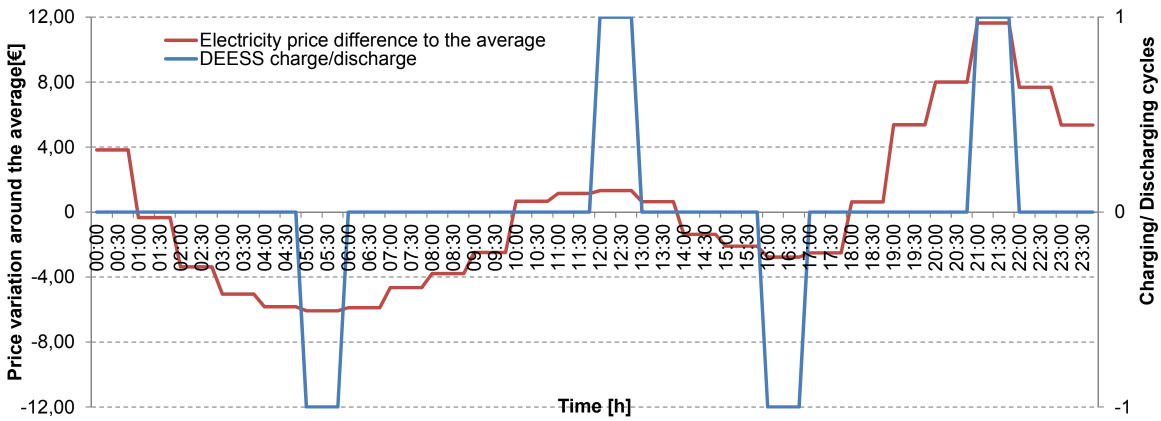

Figure 4-12 – Analysis of the energy price variation for prototype#5

The minimization of losses was performed using the load flow calculations for the network load profiles. For the case of defining the C/D profile when attempting to minimize losses, the LD can be used as a proxy due to the fact than network losses are usually strongly dependent of demand.

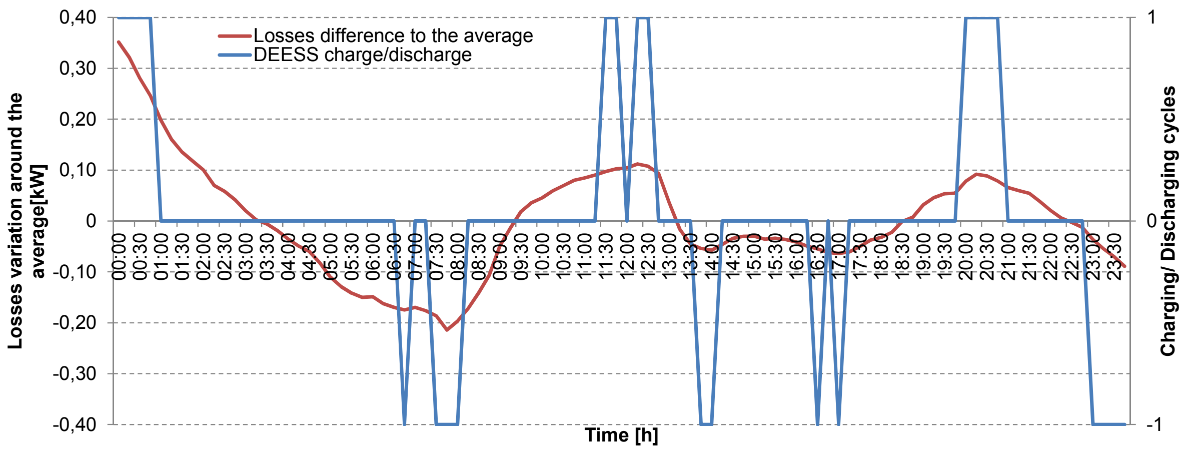

Figure 4-13 – Analysis of the variation of NEL for prototype#1

The renewable generation integration, in particular wind generation, required a different type of analysis. The main motivation for using energy storage for renewable generation resides in storing energy during high power generation periods and delivering it during low power generation periods, in order to stabilize the net distributed power injection profile. Since both generation and load diagrams were subject to a normalization procedure during the clustering process, a measure of the renewable generation availability was obtained from the difference between the average LD profile and renewable generation prototypes as represented in Figure 4-14.

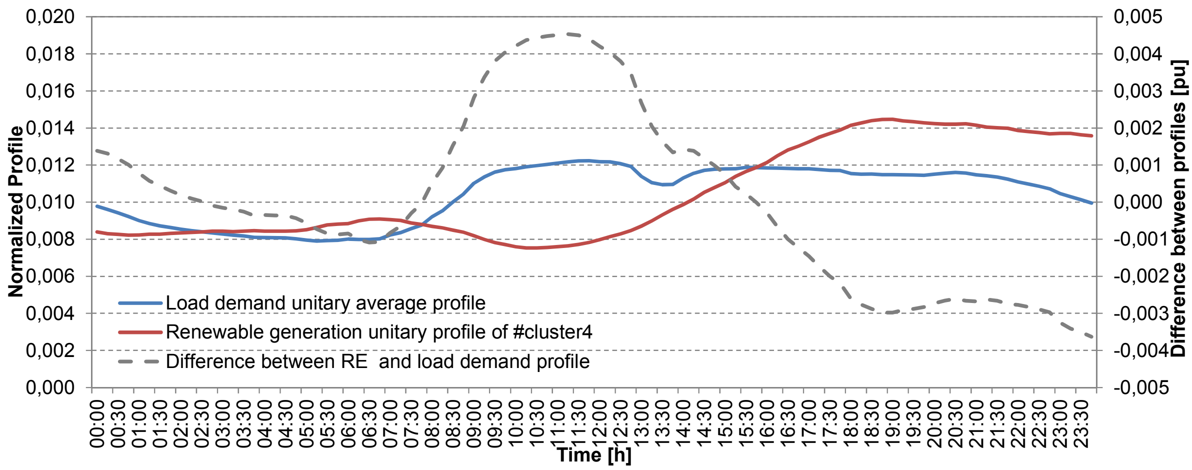

Figure 4-14 –Example of renewable power generation availability assessment when combining average annual LD and renewable cluster#4

Based on the variation, the following procedure to obtain the C/D binary vector is similar to previous scenarios as presented in Figure 4-15.

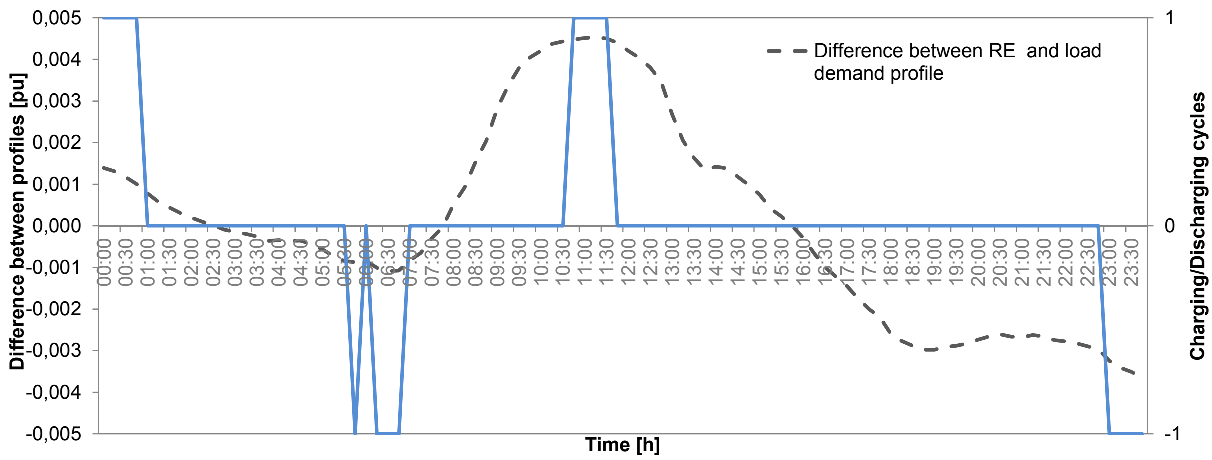

Figure 4-15 –Renewable integration considering variation between average LD combined with wind generation cluster#4

This procedure was repeated for every possible combination among prototypes. The developed combinations were as follows:

1. Combination of the five energy market rates prototypes with the five possible distribution LD prototypes, using the respective C/D developed binary vectors considering management scheme A. This step resulted in 25 scenarios.
2. Combination of the five energy market rates prototypes with the five possible distribution LD prototypes, using the respective C/D developed binary vectors considering management scheme B. This step resulted in 25 scenarios.
3. Combination of the five energy market rates prototypes with the five C/D developed binary vectors considering management scheme C. This step resulted in 25 scenarios.

It is important to note that for the third case the C/D developed binary vectors resulted from combining the five wind generation prototypes with the annual average energy LD.

Considering the time definition for charging and discharging the storage units, the information was converted into a C/D matrix to be used in the iNSGA-II during the optimization process.

4.5 Model constraints

The operation of ESS is constrained by the individual capacities of each storage unit which was specified considering the required voltage for the power inverter, a power limit which considers the minimum values of the bus capacities in the case study, and the physical limit of each individual storage solution for a maximum volume of $1m^3$.

4.6 Results and discussion

Due to the important influence of the data used in the study, the clustering process is detailed in section 3.1, showing to be an adequate method to obtain representative data of real and specific location behaviors. Nevertheless, in order to help assessing the results associated to each management scheme, a data analysis of the used data should be performed.

The combination of prototypes, e.g. those regarding LD and energy market rates, does not have a specific annual representativeness, although each considered prototype represents real behaviors. Therefore, the performed combinations should be considered as possible scenarios whose relevancies will be different and can be assessed. For the sake of demonstrating the application of the proposed methodology, and for the sake of simplicity, the weights assigned to the scenarios were considered equal.

Searching a similarity among obtained prototypes revealed that the market prices prototypes #4 and #3 were similar to the LD prototype #4, as shown in Figure 4-16 and Figure 4-17, respectively. Nevertheless, a small dissimilarity was observed during the afternoon and end of the day, when load and prices vary with opposite trends.

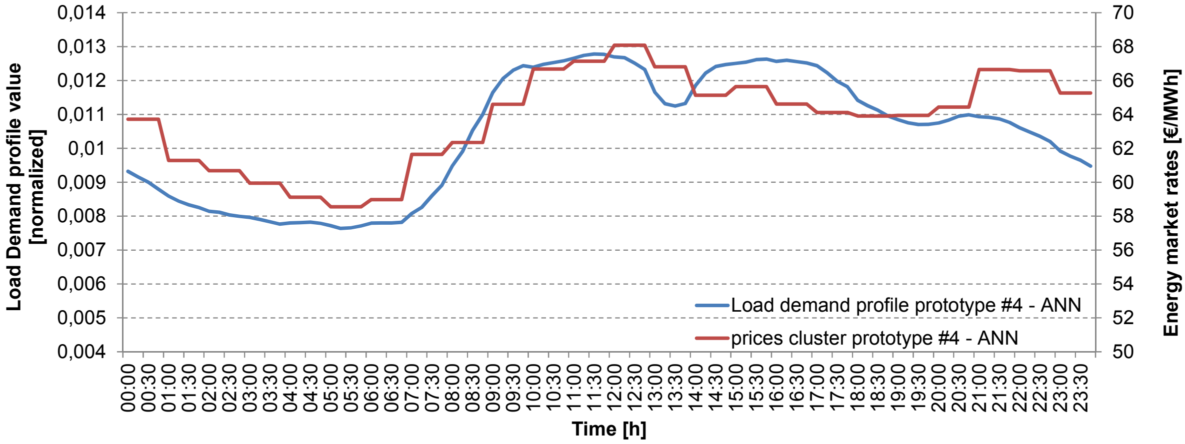

Figure 4-16 – Profile analysis of LD prototype #4 and market price prototype #4

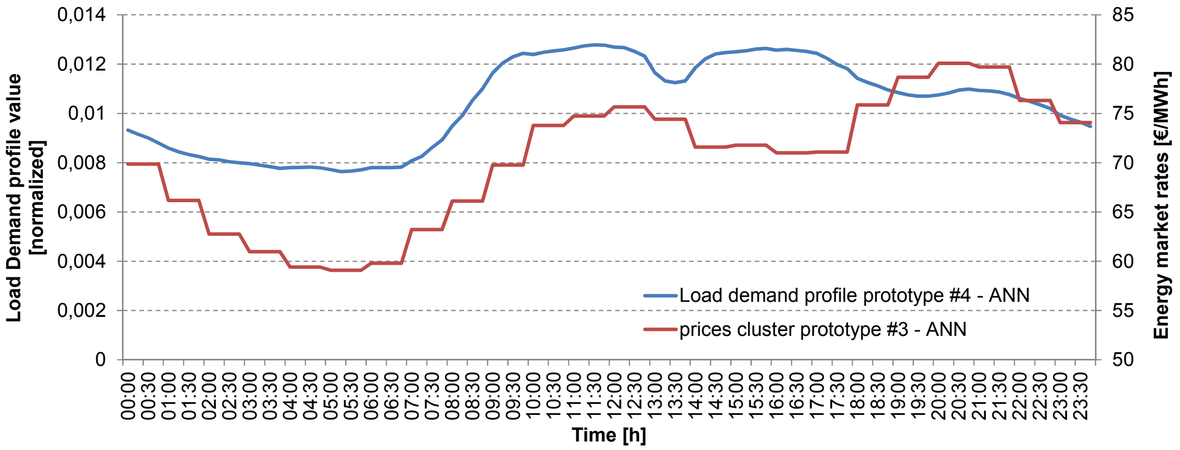

Figure 4-17 –Profile analysis of LD prototype #4 and market price prototype #3

Moreover, the average annual LD profile and market price prototypes also showed some dissimilarity, as shown in Figure 4-18, mainly due to the non-representativeness of the LD of the particular substation used regarding the global LD which influences the national energy market prices.

Since most players of the energy sector react to price stimuli, this dissimilarity may lead to non-optimal grid management on a local level. This phenomenon indicates that it may be more adequate to use a local price scheme, adapted to the cost of supply near consumption in order to avoid the use of DEESS with negative consequences to the electricity grid.

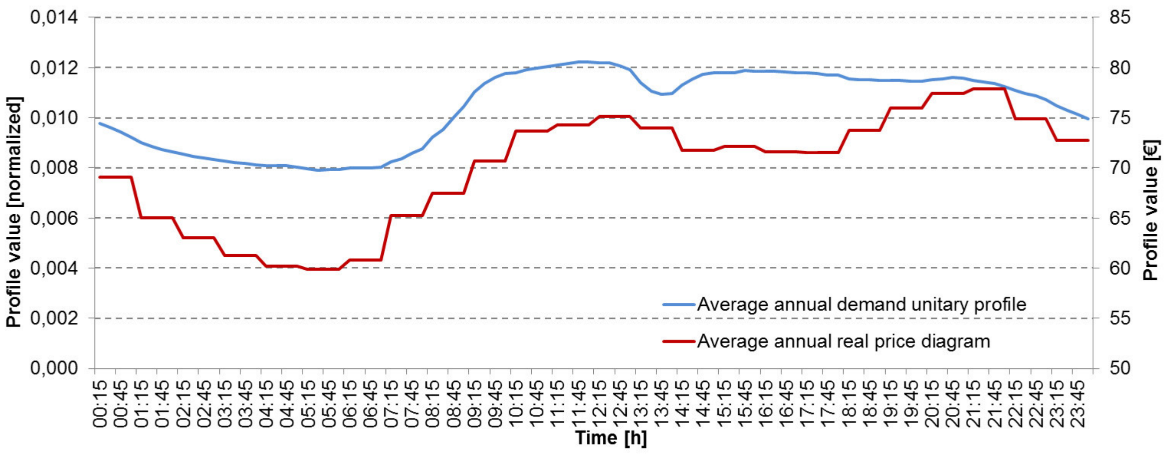

Figure 4-18 – Annual average profiles comparison of LD with energy market rate prices for 2008

Considering the multiobjective nature of the problem, the choice of a specific solution needs to be performed, e.g. using one of two methods: (i) aggregation of objectives using a weighted sum of the individual objective function values or (ii) an interactive analysis of the Pareto front.

When using the aggregation of objectives, the DM has to establish tradeoffs or preferences by setting weights for the different objective function. An interactive search is the most suited way to perform a multiobjective analysis(J. N. Clímaco et al., 2003) as it enables the DM to assess the impact of each pair of objective function results without hiding information. It was the option selected for this study because it provides the DM with all possible options and does not require the DM to freezes his/her preferences as a set of numbers or as a set of mathematical expressions defining utility functions. This method is further detailed in the following subsection.

4.6.1 DM interactive search

As a first step, an analysis of the Pareto fronts is performed, providing the DM with 2D representations, combining different pairs of objective functions. This procedure helps the DM in his assessment of associated impacts, especially when more than three objective functions are present (where the amount of data can hinder the analysis).

Figure 4-19 shows an example of possible boundaries established by the DM. When the DM establishes boundaries for some objective functions, the remaining available results are affected. By applying this type of search, the DM can check the influence of possible choices and therefore establish different tradeoffs.

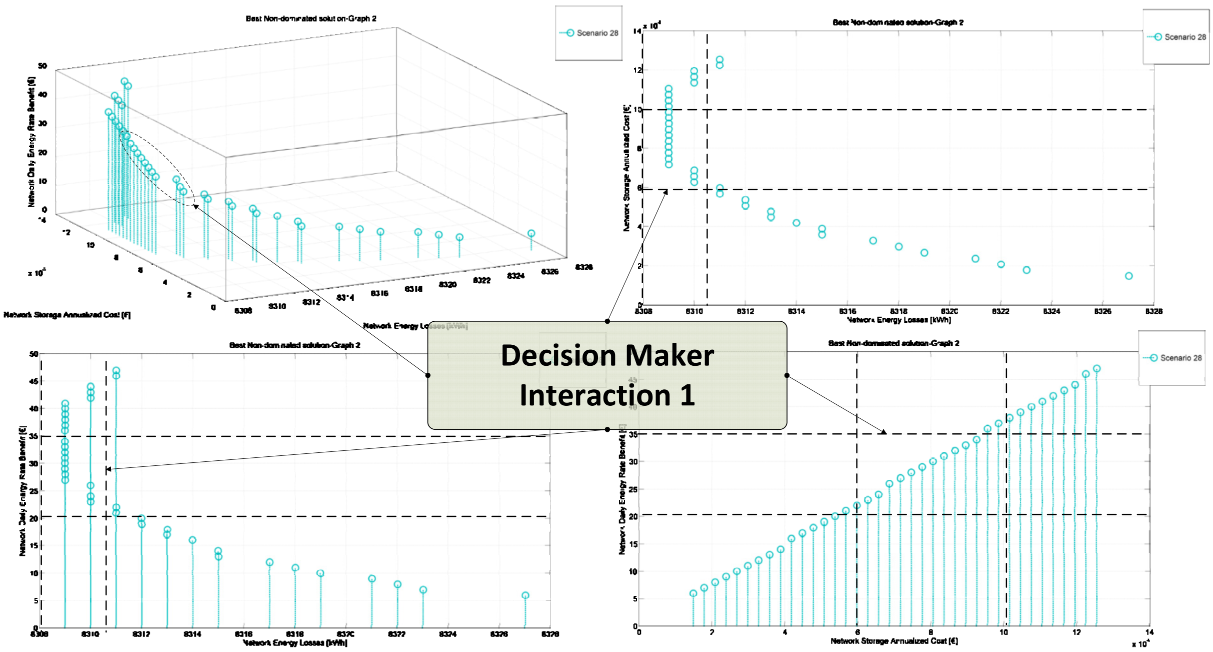

Figure 4-19 – Interactive example for scenario 28 result analysis

Although different DMs were considered, i.e., possible stakeholders/agents in the energy market each with its own multiple specific preferences, the most plausible situation is that only one of such agents will decide to invest in a storage system in a particular network. As such, this analysis is intended to solve the problem considering only one perspective at a time, defining choices regarding the definition of the C/D schedule, as well as the interactive analysis of the resulting Pareto front. To provide the DM with reference points in the Pareto front, two possible methods are described in the next subsection.

4.6.2 Reference points

Different weights might be defined for each objective function depending on the DM preferences. However, it should be noted that defining the weight for each objective function, *a priori* or *a posteriori*, may hide the global view of admissible solutions requiring a blind establishment of tradeoffs. In order to provide reference points to the DM, and help the search for the final solution two possible methods are considered:

i) providing the solutions according to the highest and smallest “crowding” value for the rank 1 set of non-dominated solutions; or

ii) providing the solution which has the minimum Euclidian distance to the optimal Pareto front available point.

4.6.2.1 Crowding distance method

The crowding distance, presented in (Deb et al., 2002), represents the absolute normalized difference in the function values of two adjacent solutions. For boundary solutions, namely solutions with smallest and largest function values, an infinite distance value is assigned, while for crowded results this operator converges to zero.

An application of the crowding distance is exemplified in Figure 4-20, where extreme solutions and the highest density region are highlighted on the Pareto front. Solutions are distinguished by assigning infinity and zero values to the crowding distance of solutions at the boundaries of Pareto front and of solutions in the center of high density regions, respectively.

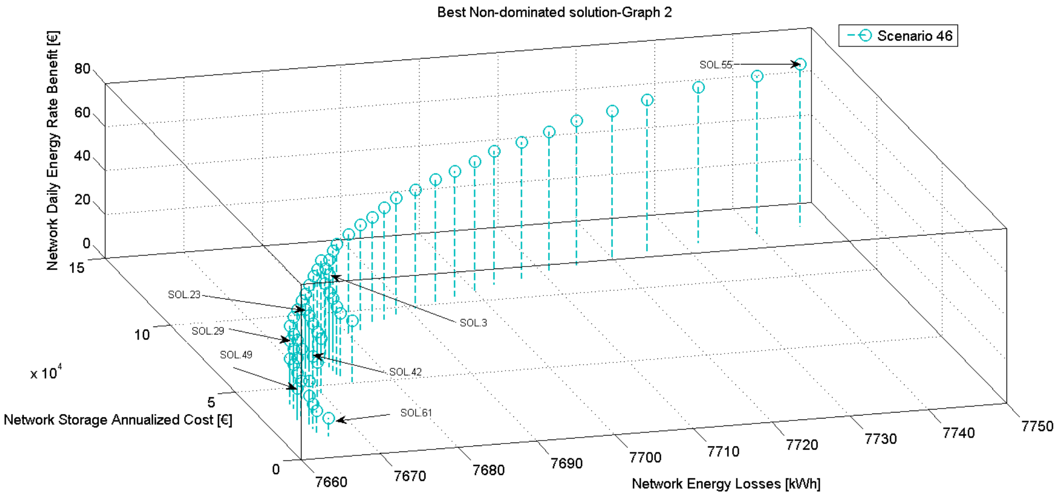

Figure 4-20 – Crowding distance highlights for Pareto-front of scenario 46

Figure 4-20 shows the boundary solutions number 3, 49, 55 and 61 and the highest density solutions (more crowded) number 23, 29 and 42 which presented the value infinite and nearly zero, respectively. The crowding-distance operator should only be used as a tool to help the DM search, as it indicates the location of important points such as the boundary, inflexion and higher density location results. This method allows the DM to consider the four objective function results, even when one of them becomes irrelevant or with an insignificant variation.

Table 4-7 – Crowding evaluation parameters of scenario 28

Non-dominated solution	Evaluation parameters		Non-dominated solution	Evaluation parameters	
N.º	**rank**	**crowding**	**N.º**	**rank**	**crowding**
1	1	Inf	21	1	0.213947854
2	1	0.102836743	22	1	0.102836743
3	1	0.182782543	23	1	0.158392299
4	1	0.127226987	24	1	0.158392299
5	1	0.102836743	25	1	0.26949436
6	1	0.127226987	26	1	0.102836743
7	1	0.158392299	27	1	0.102827693
8	1	0.102836743	28	1	0.102827693
9	1	0.158392299	29	1	Inf
10	1	0.158383249	30	1	0.102827693
11	1	0.102827693	31	1	0.26950341
12	1	0.102836743	32	1	0.213947854
13	1	0.102827693	33	1	0.380614521
14	1	0.127226987	34	1	0.213947854
15	1	0.102836743	35	1	0.182782543
16	1	0.182782543	36	1	0.127226987
17	1	0.26949436	37	1	0.158392299
18	1	0.238338098	38	1	Inf
19	1	0.102827693			
20	1	0.102836743			

Table 4-7 presents the Rank 1 results for scenario 28, considering a more linear example. As can be observed, there are three solutions with a crowding parameter equal to infinite where the DM should focus his analysis. Among the three or more possible solutions, two of them are the extremes of the Pareto front. Figure 4-21 presents the extreme solutions 29 and 38, and solution 1 as the inflexion point in the Pareto front.

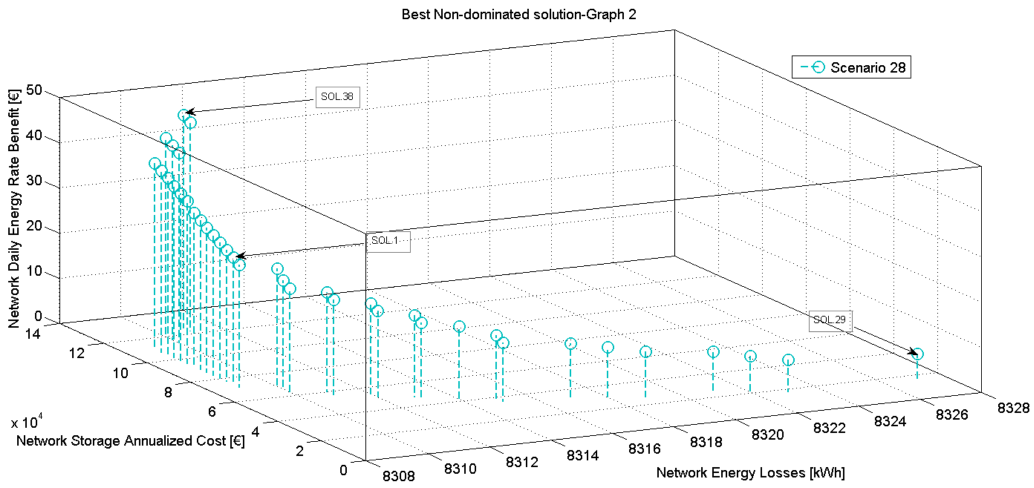

Figure 4-21 – Crowding distance method application in scenario 28 to help choosing the best balanced non-dominated solution

4.6.2.2 Euclidian Distance method

Searching for the minimum Euclidian distance to the optimal Pareto front available point might be easier to understand. However, its calculation may need the definition of different weights for each objective function, something that can only be defined by the specific DM.

For the current case study only three objective functions were considered, namely the NEL, the NSAC and the NERB, as the NVqmd has a low variation among the majority of scenarios. For the sake of simplicity equal weights were assigned for the different objectives.

Applying the Euclidian distance method to find a reference point, as presented in equation (23), requires a normalization of all the tree objective functions.

$$\|Dist\|_2 = \sqrt{\sum_{i=1}^{3} w_i[\Delta Obj_i - Max.(\Delta Obj_i)]^2} \tag{23}$$

The Euclidian distance to the optimal point of the Pareto front defined by the NEL, NSAC and NERB objective functions ($\|Dist\|_2$) used the variation range of each objective function ΔObj_i, such as the NEL and the NSAC, which is calculated using equation (24), and a weight factor (w_i) to consider the annual representativeness of each scenario.

$$\Delta Obj_i = \frac{Obj_i}{Obj_{i,MAX} - Obj_{i,min}}, i = 1,2,3; \qquad (24)$$

The variation range is calculated considering each objective function value divided by the same objective function range of the Pareto front results, namely the maximum minus the minimum obtained value.

Table 4-8 presents the results of the described normalization process for the same scenario 28 example: the C/D profile obtained from combining the LD prototype#3 and the energy rate prototype#1 for the MSch B goal, is applied.

Table 4-8– Euclidian normalized distance for the scenario 28 non-dominated solutions

Non-dominated solution	**Euclidian normalized distance**	**Non-dominated solution**	**Euclidian normalized distance**
N.º	(NERB,NSAC,NERB)	N.º	(NERB,NSAC,NERB)
1	0.7120	21	1.0194
2	0.7340	22	0.9257
3	0.7086	23	0.7742
4	0.7775	24	0.8111
5	0.7175	25	1.1446
6	0.7709	26	0.8550
7	0.7648	27	0.7468
8	0.7951	28	0.7083
9	0.7406	29	1.4142
10	0.7988	30	0.9019
11	0.7571	31	1.0652
12	0.7447	32	0.9136
13	0.7249	33	1.2480
14	0.7272	34	1.1956
15	0.8139	35	0.9504
16	0.8976	36	0.9796
17	0.9760	37	0.8772
18	0.8414	38	1.0062
19	0.8340		
20	0.7299		

Solution number 28 had presented the smallest distance to the “ideal optimal point” (meeting the considered weights), providing a “balanced“ solution in the Pareto front but which acceptance by the DM will depend of the implied tradeoffs, as shown in Figure 4-22.

Comparing the solutions obtained with the Euclidian distance and crowding distance method, both methods pointed to nearby areas. Both methods give an important reference to the DM, the crowding distance not requiring additional data manipulation or weight definition.

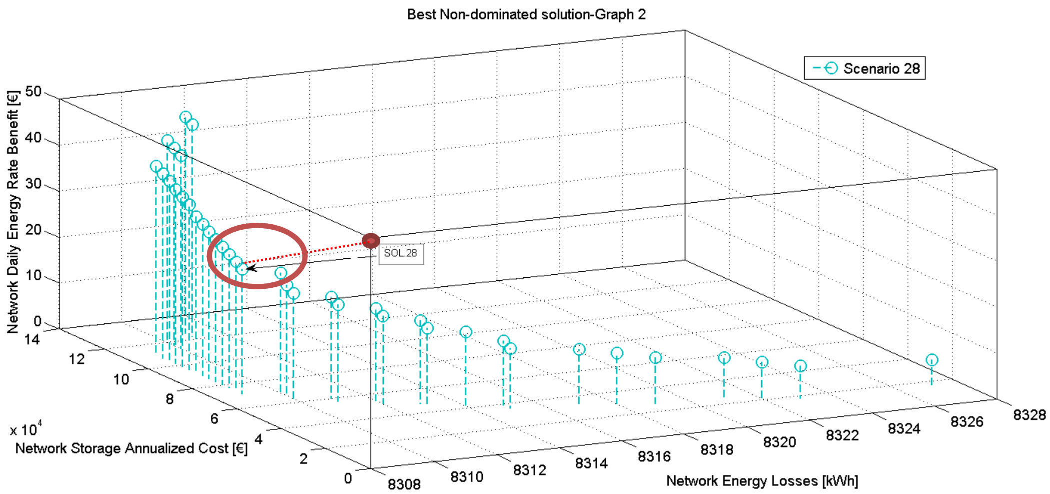

Figure 4-22 –Euclidian distance method application in scenario 28 to help choosing the best balanced non-dominated solution

4.6.3 Results analysis

In order to have comparison values for each scenario, a first analysis was performed considering the system without energy storage and obtaining the reference values of losses (NEL) and voltage quadratic mean deviations (NVqmv), as presented in Table 4-9.

Table 4-9 – NEL and NVqmd values for the RDS without storage

Scenarios	**NVqmd [pu]**	**NEL [kWh]**
1,2,3,4,5	0.1012	7 670.98
6,7,8,9,10	0.1012	7 705.60
11,12,13,14,15	0.1012	8 334.89
16,17,18,19,20	0.1012	7 725.51
21,22,23,24,25	0.1012	7 232.95
26,31,36,41,46	0.1012	7 670.98
27,32,37,42,47	0.1012	7 705.60
28,33,38,43,48	0.1012	8 334.89
29,34,39,44,49	0.1012	7 725.51
30,35,40,45,50	0.1012	7 232.95
51,52,53,54,55	0.1012	8 431.06
56,57,57,58,59,60	0.1012	8 431.06
61,62,63,64,65	0.1012	8 431.06
66,67,68,69,70	0.1012	8 431.06
71,72,73,74,75	0.1012	8 431.06

The final results were obtained applying a genetic algorithm with a population of possible solutions composed by 150 individuals, and a maximum number of 100 generations, assuring convergence. Results regarding the MSch A, MSch B and MSch C impacts are summarized in Appendix chapter (Table 7-1, Table 7-2, Table 7-3, respectively). In order to simplify the numerical analysis, only the maximum and minimum values for each scenario are presented in the summarized tables. Table 4-10 presents the global analysis.

Results show that the MSch B returns higher NERB results when compared to MSch A. Although not strong, the bias between the substation LD (and consequently with network power losses) and energy market prices will contribute to reduce the reluctance of DSO in integrating resources out of his control (Sovacool & Hirsh, 2009), even if the stakeholder objective is only economic.

The maximum obtained NERB daily results were 60€, 76€ and 54€, the best results associated to MSch A and MSch B showing the importance of energy prices being closely aligned with actual delivery costs, mostly dependent on local load magnitude. The use of an economic objective may present technical problems in managing the network if the local consumption is not correlated with energy market prices.

MSch B presented the highest NEL reductions of 52.95kWh/day whereas MSch A and MSch C obtained the maximum of 43.95kWh/day and 14.06kWh/day, respectively.

MSch C had the smallest economic income and NEL reduction. These results can be explained considering the obtained prototypes during the clustering stage, in which the obtained wind generation prototypes showed no correlation with market energy prices and the substation LD. Therefore, the suited C/D periods may introduce some pressure into the network in periods of high demand.

Table 4-10 – Summarized analysis for the three considered management schemes

		NEL [kWh/day]		NVqmd [p.u.]		NSAC [€]		NERB [€]		NSACvsNERB [%]	
		Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.
MSch A	Original Values	7 232.95	7 670.98	0.101	0.101						
	Improvements	-43.95	0.02	-0.001	0.018	5 973	140 359	1.00	60.00	0.021%	0.047%
	Simulation n.º	24	1	10	25	24	22	24	15	19	5
	Variation [%]	-0.61%	0.00%	-1.22%	17.55%						
	N.º Units [un.]					2	47				
MSch B	Original Values	7 232.95	7 670.98	0.101	0.101						
	Improvements	-52.95	-5.98	-0.002	0.000	5 973	140 359	1.00	76.00	0.017%	0.055%
	Simulation n.º	45	26	26	28	40	36	40	36	50	46
	Variation [%]	-0.73%	-0.08%	-2.21%	-0.23%						
	N.º Units [un.]					2	47				
MSch C	Original Values	8 431.06	8 431.06	0.101	0.101						
	Improvements	-14.06	-2.06	0.000	0.002	8 959	140 359	2.00	54.00	0.012%	0.041%
	Simulation n.º	61	71	51	69	62	70	60	66	75	66
	Variation [%]	-0.17%	-0.02%	-0.23%	1.74%						
	N.º Units [un.]					3	47				

From the 75 performed simulations, roughly 70% (53 simulations) presented a defined convex curve, showing that an increase in the ESS capacity may not correspond to a linear improvement of the optimization parameters. In fact, most of the non-dominated solutions presented a point or zone (i.e. turning point) in which the objective functions cease to improve.

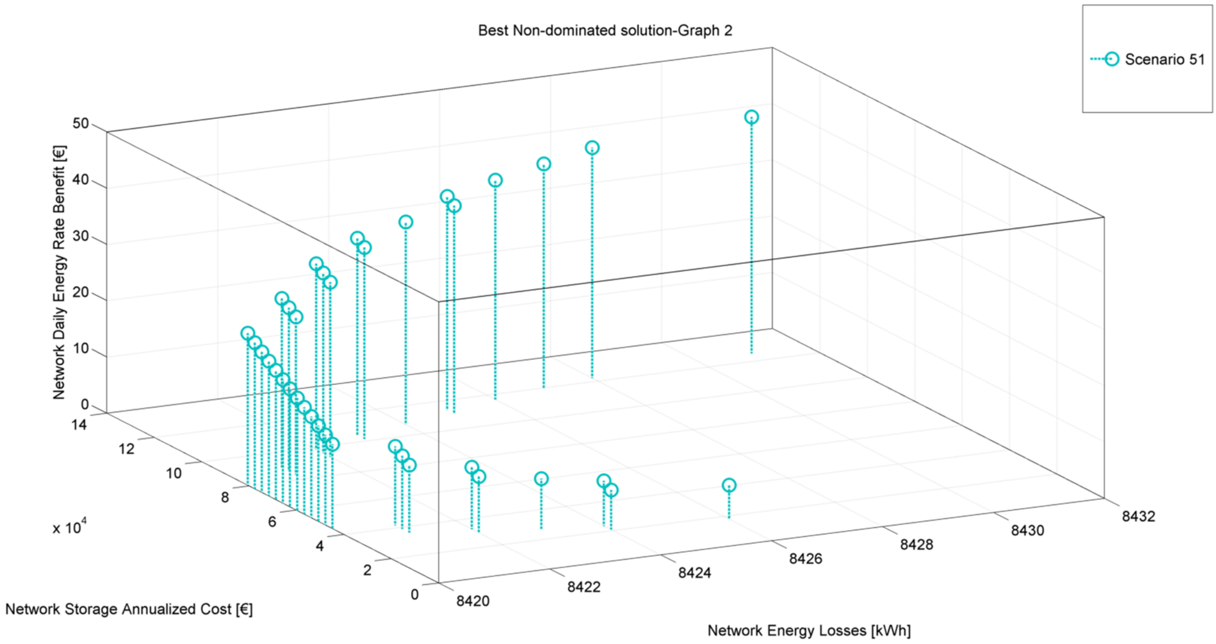

Figure 4-23 – Isometric view of scenario 51 results (Scheme 3)

Considering the distribution example presented in Figure 4-23, for scenario 51, which combines the renewable generation prototype#1 with the average annual LD when using the energy market price prototype #1, the turning point for NEL optimization can be observed. Regarding the original NEL (without ESS) of 8 431.06 kWh/day, all the non-dominated solutions enable a NEL reduction. However, if the objective is to minimize NEL, some solutions should be rejected due to their small impact.

This type of methods has the advantage of allowing the DM to choose solutions by setting tradeoffs, since among the minimum NEL solutions there are several possible choices. Figure 4-24 shows the NERB versus NEL results for scenario 51 (MSch C - Renewable integration), illustrating the turning point/zone for NEL optimization.

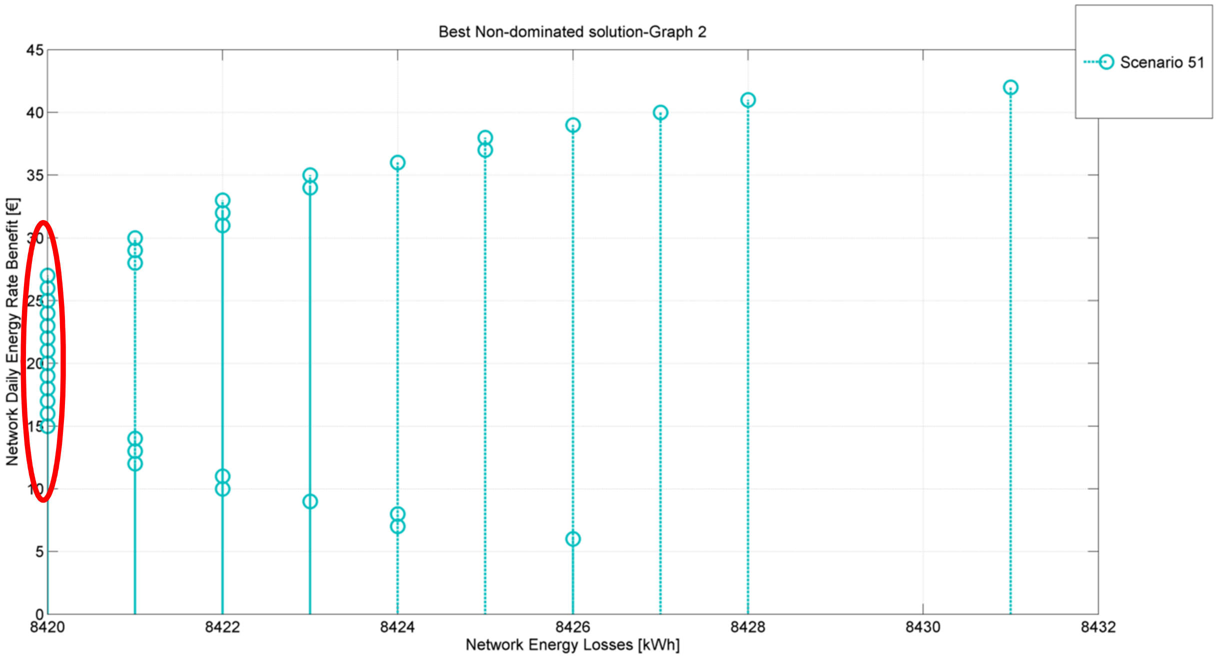

Figure 4-24 – 2D view of Scenario 51 by comparing NERB and NEL results

As shown in Figure 4-25, several solutions could be chosen (varying the NERB between 14€ and 28€ per day) for the same final NEL result of 8 420 kWh/day.

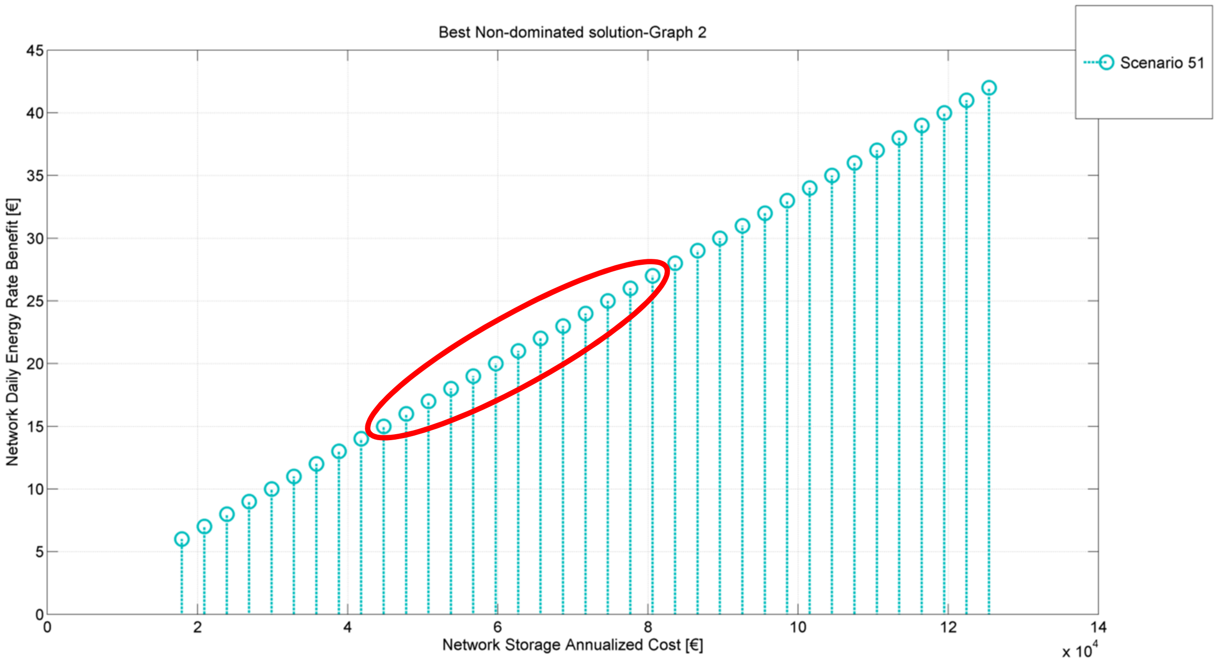

Figure 4-25 – 2D view of Scenario 51 by comparing NSAC and NEL results

Based on the information provided in Figure 4-24 and Figure 4-25 the DM chooses the most favorable solution (e.g., by establishing an investment limit).

A significant NVqmd variation among non-dominated solutions was observed in simulation scenarios 15, 20 and 25, regarding the MSch A and simulation scenarios

69 and 70 and 74, regarding the MSch C. Except for scenario 74, the aforementioned simulations have in common the related number of C/D periods. Scenarios 68, 71, 72 and 73 also presented an increase in NVqmd, when compared with the original values, but, to smaller values.

On average, the DEESS produced an increase of the NVqmd (by 0.0050 pu), while the remaining scenarios showed a slight reduction of the NVqmd (by 0.0007 pu). The increase was higher (about 0.0168 pu) for the MSch A scenarios 15, 20 and 25. In the MSch C, the NVqmd increased (by 0.0011pu) in 36% of the studied scenarios.

All the mentioned C/D profiles have in common the existence of two charging and discharging periods, increasing the probability to charge and discharge in critical capacity periods.

In the MSch B scenarios, the NVqmd did not present a significant variation of the non-dominated solutions. Maybe due to the best match of the C/D periods along the diagram. Moreover, the solutions with smaller impacts regarding the NVqmd where related with higher daily C/D cycles scenarios (i.e. equal to three), namely in scenario 26,31,36,41 and 46.

The Pareto front distribution of solutions of scenario 20 and scenario 31 is represented in Figure 4-26 and Figure 4-27, respectively. Detailed information about each scenario best NVqmd is presented in Table 4-11.

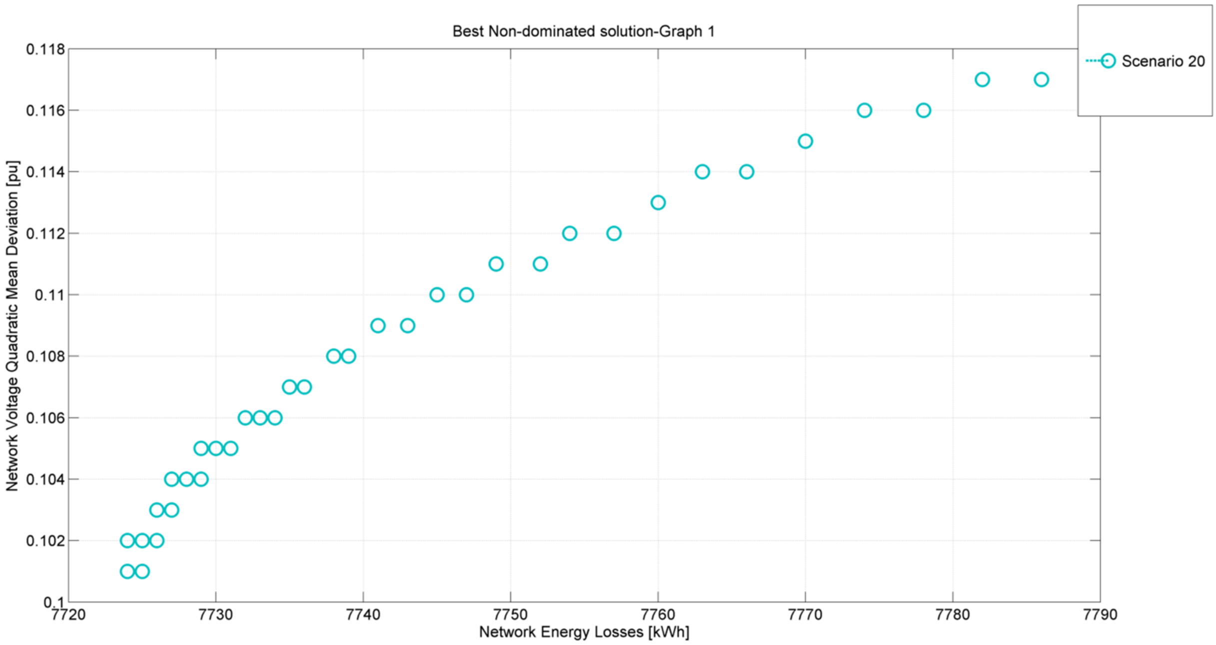

Figure 4-26 – 2D view of Scenario 20 (MSch A) by comparing NVqmd and NEL results

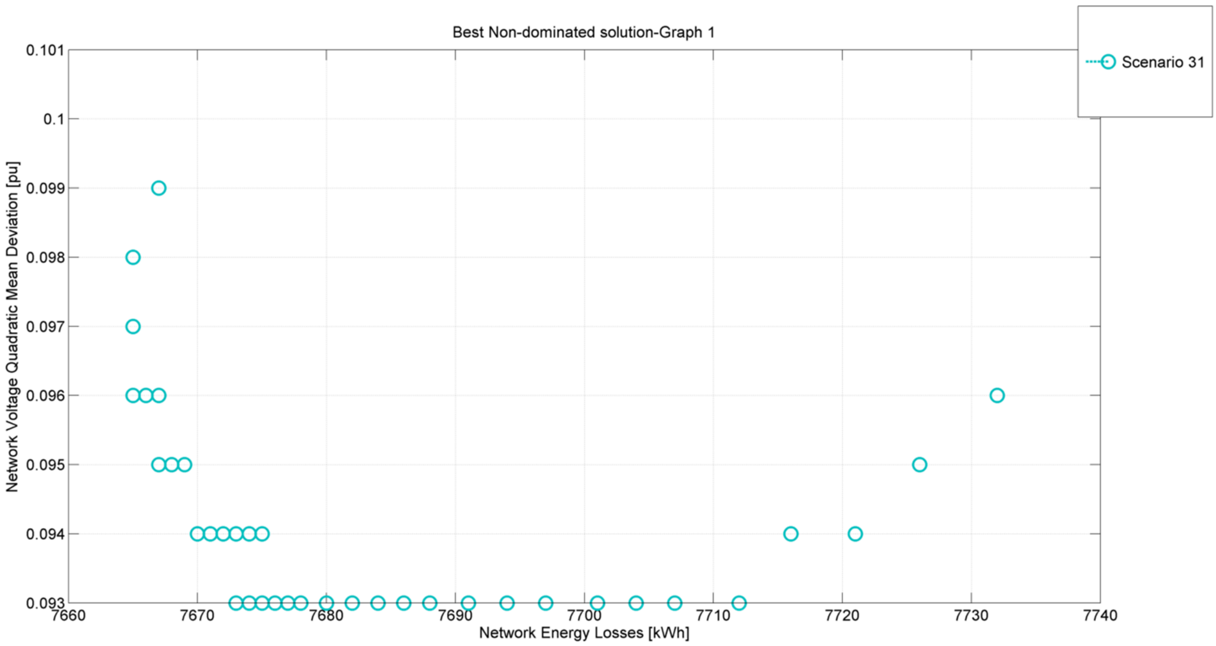

Figure 4-27 – 2D view of Scenario 31 (MSch B) by comparing NVqmd and NEL results

Table 4-11 – NVqmd impacts per scenario

Scenario	NVqmd	NVqmd improv.	Disch.	Charg.	Disch.	Charg.	Scenario	NVqmd	NVqmd improv.	Disch.	Charg.	Disch.	Charg.
	[pu]	[pu]	[%]	[%]	[pu]	[pu]		[pu]	[pu]	[%]	[%]	[pu]	[pu]
1	0.101	0.000	-9.4	12.2	-0.008	0.009	29	0.101	-0.001	-8.4	15.0	-0.008	0.009
2	0.101	0.000	-9.8	13.0	-0.009	0.009	34	0.101	-0.001	-9.8	17.6	-0.010	0.010
3	0.101	0.000	-9.4	12.4	-0.008	0.009	39	0.101	-0.001	-9.4	16.9	-0.010	0.010
4	0.101	0.000	-9.6	12.8	-0.008	0.009	44	0.101	-0.001	-9.0	16.1	-0.009	0.009
5	0.101	0.000	-8.6	11.0	-0.007	0.008	49	0.101	-0.001	-9.2	16.4	-0.009	0.009
6	0.101	0.000	-8.9	13.0	-0.008	0.009	30	0.101	-0.001	-9.5	22.2	-0.010	0.009
7	0.101	0.000	-8.7	13.2	-0.009	0.009	35	0.101	-0.001	-9.8	23.0	-0.010	0.010
8	0.101	0.000	-9.1	13.9	-0.009	0.009	40	0.101	-0.001	-9.1	21.3	-0.009	0.009
9	0.101	0.000	-10.3	14.5	-0.009	0.010	45	0.101	-0.001	-10.1	23.8	-0.010	0.010
10	0.101	-0.001	-8.3	11.7	-0.008	0.008	50	0.101	-0.001	-10.5	24.8	-0.011	0.010
11	0.101	0.000	-9.4	16.2	-0.009	0.009	51	0.101	0.000	-8.9	13.5	-0.009	0.009
12	0.101	0.000	-9.0	15.1	-0.009	0.009	52	0.101	0.000	-9.8	14.9	-0.010	0.010
13	0.101	0.000	-9.5	16.0	-0.009	0.009	53	0.101	0.000	-9.7	14.6	-0.009	0.010
14	0.101	0.000	-9.2	15.7	-0.009	0.009	54	0.101	0.000	-10.0	15.2	-0.010	0.010
15	0.101	0.017	-7.4	10.3	-0.007	0.008	55	0.101	0.000	-9.9	15.0	-0.010	0.010
16	0.101	0.000	-10.4	16.2	-0.009	0.009	56	0.101	0.000	-8.7	13.1	-0.009	0.009
17	0.101	0.000	-10.4	16.4	-0.009	0.009	57	0.101	0.000	-9.9	15.0	-0.010	0.011
18	0.101	0.000	-10.3	16.1	-0.009	0.009	58	0.101	0.000	-9.1	13.7	-0.009	0.010
19	0.101	0.000	-9.1	16.0	-0.009	0.009	59	0.101	0.000	-8.9	13.4	-0.009	0.009
20	0.101	0.016	-7.3	10.1	-0.007	0.007	60	0.101	0.000	-9.3	14.1	-0.009	0.010
21	0.101	0.000	-10.7	22.4	-0.010	0.010	61	0.101	0.000	-8.9	14.1	-0.008	0.009
22	0.101	0.000	-11.1	23.1	-0.010	0.010	62	0.101	0.000	-9.1	14.5	-0.009	0.009
23	0.101	0.000	-10.6	22.1	-0.010	0.010	63	0.101	0.000	-9.7	15.4	-0.009	0.010
24	0.101	0.000	-9.7	21.4	-0.009	0.009	64	0.101	0.000	-9.3	14.7	-0.009	0.009
25	0.101	0.018	-6.5	10.4	-0.006	0.007	65	0.101	0.000	-9.1	14.5	-0.009	0.009
26	0.101	-0.002	-8.4	11.2	-0.008	0.008	66	0.101	0.001	-9.1	12.2	-0.008	0.009
31	0.101	-0.002	-8.1	10.9	-0.007	0.008	67	0.101	0.000	-8.8	11.7	-0.008	0.008
36	0.101	-0.002	-8.8	11.7	-0.008	0.009	68	0.101	0.001	-9.6	12.8	-0.008	0.009
41	0.101	-0.002	-7.6	10.2	-0.007	0.008	69	0.101	0.002	-9.2	12.3	-0.008	0.009
46	0.101	-0.002	-8.3	11.1	-0.008	0.008	70	0.101	0.002	-9.6	12.8	-0.008	0.009
27	0.101	-0.001	-8.6	12.2	-0.008	0.009	71	0.101	0.001	-9.4	12.5	-0.009	0.010
32	0.101	-0.001	-9.0	12.8	-0.008	0.009	72	0.101	0.001	-9.2	12.3	-0.009	0.010
37	0.101	-0.001	-9.4	13.4	-0.009	0.009	73	0.101	0.001	-9.3	12.4	-0.009	0.010
42	0.101	-0.001	-8.6	12.4	-0.008	0.009	74	0.101	0.002	-10.5	14.1	-0.011	0.012
47	0.101	-0.001	-8.6	12.2	-0.008	0.009	75	0.101	0.001	-10.1	13.4	-0.010	0.011
28	0.101	0.000	-9.1	15.9	-0.009	0.009							
33	0.101	0.000	-9.9	17.4	-0.010	0.010							
38	0.101	0.000	-9.7	16.9	-0.010	0.010							
43	0.101	0.000	-9.3	16.3	-0.009	0.010							
48	0.101	0.000	-10.0	17.6	-0.010	0.010							

The influence of each C/D period in the results showed that DEESS have different impacts on each working period when compared to the same period of the network without storage. On average, the voltage deviation showed a reduction of 9.28% when discharging, and an increase of 14.89% when charging among all the seventy five tested scenarios.

Considering the results and the NVqmd objective function (which considers the maximum daily voltage deviation for each individual), a possible improvement may derive from a dynamic optimization of the C/D profile, in order to maximize the possible gain resulting from the time difference.

Among MSch B scenarios it was observed that scenarios with three C/D periods presented (namely scenarios 26,31,36,41 and 46) the smallest NEL improvement among all the studied MSch B scenarios. In fact the best results regarding the NEL used only one daily C/D cycle namely the ones tested in scenarios 30, 35, 40, 45, 50. Therefore, results showed the influence of the C/D periods in the optimization process and associated impacts.

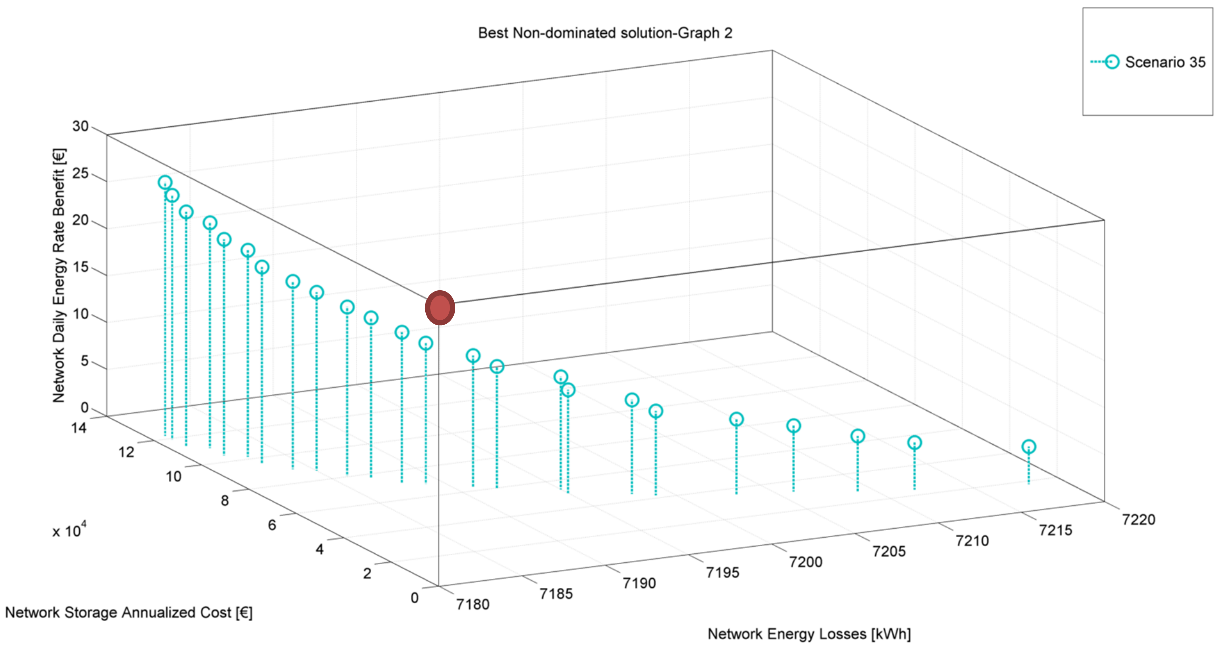

Figure 4-28 – Isometric view of scenario 35 results (MSch B)

Considering different scenarios and/or overlaying different Pareto fronts, the DM could both perform the interactive search for the optimal solution, as well as to analyze the impact range of the overlaid Pareto fronts as represented in Figure 4-29. Another possibility can be the definition of weights and the search for the minimum Euclidian distance to the ideal solution as represented in Figure 4-28.

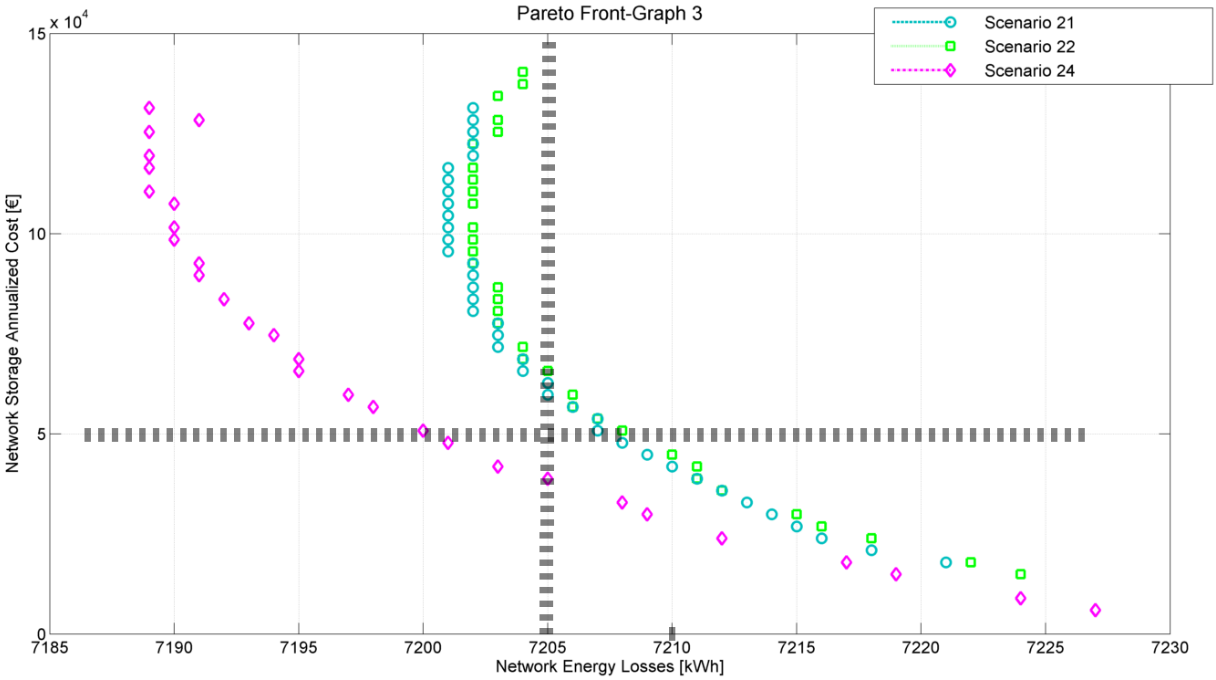

Figure 4-29 – 2D representation results for NEL, NSAC

The results for scenarios 21, 22 and 24, showed that, for solutions with similar NEL results of 7 205.0 kWh, only 9 out of 48 buses were identical (Table 4-12). The results showed that predefining the admissible buses for DEESS installation and capacity optimization, as performed in previous studies (Ippolito et al., 2014), (Fossati et al., 2015), might have limitations, because different buses may present different advantages for different energy services.

Table 4-12 – Comparison results for scenarios 21, 22 and 24 with 7 205.0kWh NEL result

	Scenarios				Scenarios				Scenarios		
Bus N.º	**21**	**22**	**24**	**Bus N.º**	**21**	**22**	**24**	**Bus N.º**	**21**	**22**	**24**
6	1	1	1	**26**	0	1	0	**49**	0	0	0
7	0	1	0	**27**	0	0	0	**50**	0	0	0
8	1	0	0	**28**	0	0	0	**51**	0	0	0
9	1	0	1	**29**	0	0	0	**52**	1	0	0
10	1	1	1	**33**	0	0	0	**53**	0	0	1
11	0	1	0	**34**	0	0	0	**54**	1	1	1
12	1	0	1	**35**	0	0	0	**55**	0	1	0
13	1	1	0	**36**	0	0	0	**59**	1	1	1
14	0	1	0	**37**	0	0	0	**61**	1	1	1
16	1	1	1	**39**	0	0	0	**62**	1	1	1
17	0	1	0	**40**	0	0	0	**64**	1	1	1
18	0	1	0	**41**	0	0	0	**65**	1	1	1
20	1	0	1	**43**	0	1	0	**66**	1	1	0
21	1	0	0	**45**	0	0	0	**67**	0	0	0
22	1	1	0	**46**	1	0	0	**68**	0	1	0
24	0	0	0	**48**	1	0	0	**69**	1	1	0

Figure 4-29 shows the two-dimensional analysis for NEL and NSAC. For similar NSAC, different NEL could be obtained, depending on the C/D profile definition. Again, the choice of the solution among the set of non-dominated solutions of Pareto front requires an analysis by the DM. As an example, a line can be drawn with a constant NSAC (as shown in Figure 4-29), which represents the maximum admissible investment level to be considered. The intersection of the line with a bi-dimensional Pareto front, might be a potential solution for the DM. The corresponding location for the storage units can then be represented on the network topology scheme, as presented in Figure 4-30 or as presented in Table 4-12, where the assignment of units is marked with “1”.

For the specific DM preferences used in the example, repeated DEESS locations were obtained for different management schemes (namely in nodes 54, 55, 59, 61, 62, 64, and 69).This behavior pattern reveals the most critical nodes in the network in which storage obtained the best results, according to the stated preferences.

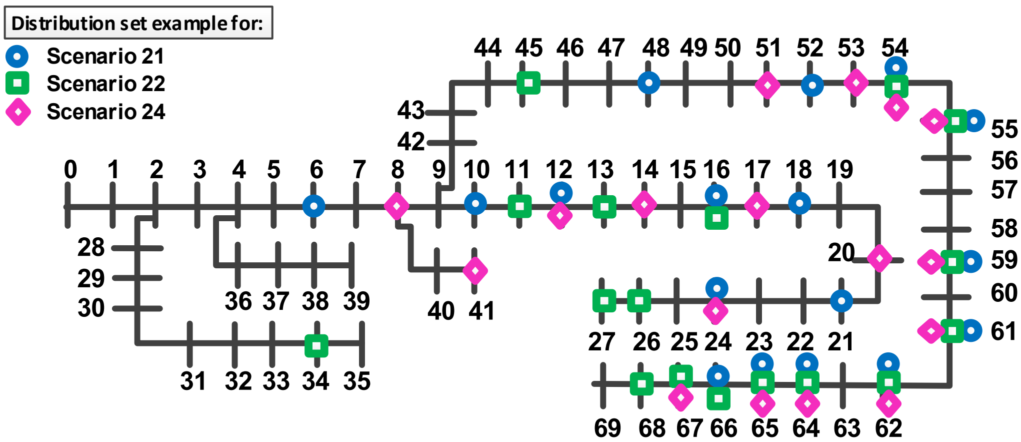

Figure 4-30 – Location set for DEESS installation considering three different management schemes

The obtained results in MSch B were not economically appealing, since the highest results (associated with scenario 36), only achieved around 76 €/day, roughly 27 740 €/year, for a total estimated annualized cost of 140 359 €.

The results are aligned with previous proposals (Eyer et al., 2004), (Kempton & Tomić, 2005) to combine benefits, in order to increase the final energy storage benefit (e.g., reducing the GHG emissions or providing regulation services).

4.6.4 Externalities: avoided GHG

The EEX auction platform is hereby used as the reference for emission allowances, in order to obtain real data of GHG costs commonly accepted by the majority of European countries. The EU ETS is a policy to combat climate change and reduce industrial GHG emissions. This is currently the largest international system for trading GHG emission allowances, covering more than 11 000 power stations and industrial plants (in 31 countries), and it uses auctioning as the basic principle to allocate allowances (Commission, 2015e), (EEX, 2014). In 2013, more than 40% of all allowances were auctioned, and these figures are expected to increase in the following years. The role of transitional common auction platform to deploy the use of allowances has been awarded by EEX (on behalf of 24 Member States and Poland) during a transitional period.

The environmental assessment is performed based on the following assumptions:

- The reference price for emissions is an annual average price;
- The avoided emissions are established *a priori* by the DM, considering available conventional power plants for energy regulation (such as coal and natural gas); and
- Avoided emissions calculation should use the efficiency of the specific power plant;

Since efficiency depends on specific power plant characteristics, the efficiency indicators for Portuguese power plants (ERSE, 2012) are considered, to obtain the associated emissions. Therefore, in order to calculate GHG emissions for the case study task, the following data and assumption were considered:

- Allowances annual average price ($AAAP$) in 2013: 4.19 [€/t CO_2];
- Avoided power plant technology: Coal;
- Power plant emission factor (PP_{ef}): 897 [g/kWh];
- The charged energy in the DEESS is obtained from a RE source.

Choosing a technology to be partially replaced by DEESS should account for the market offer. However, due to data limitations, the study assumes an avoided power plant technology.

The avoided GHG emissions are calculated using equation (25) where E_{dch} relates the DEESS discharged energy to the network.

$$GHG\ [tCO2] = \frac{E_{dch} \times PP_{ef}}{10^6} \tag{25}$$

Hence, the daily avoided cost in GHG emissions ($COST_{GHG}$) is calculated using equation (26).

$$COST_{GHG}[€/day] = GHG \times AAAP \tag{26}$$

As an example, the solution obtained with minimum Euclidian distance to each Pareto front for all the 75 scenarios (see section 4.6.2), resulted on an average daily GHG reduction of 0.593 tCO_2/day with an estimated avoided cost of 2.48 €/day (905.20 €/year) not enough to obtain a positive net benefit. The results were obtained considered the same avoided cost for all the 365 days and average discharge energy of 27.80 kWh/day.

Since the CO_2 price was indexed to the annual average price of allowances in the EU ETS and considering the worldwide economic crisis, it may be expectable that the economic value of allowances would increase, as result of the expected economic growth, augmenting the positive impact of ESS and consequently the economic viability of those systems.

4.6.5 Power regulation services (availability for frequency control)

Even with a surplus tariff, the cost and the efficiency of storage devices is the cause of a not sufficiently attractive revenue, showing that significant efficiency improvements are needed if the operational advantages of DEESS are to be matched within a real business opportunity. For example, in scenario 36 the annualized cost for the highest NERB results was 140 359 €/year, far larger than the daily benefit of 76 € (roughly 27 740 €/year). However, results showed that DEESS may play an important role in the power regulation market since it could reduce roughly an average of 904 kVA (19.42%) when discharging the batteries, and increase LD by 1 110kVA (23.82%) when charging. Figure 4-31 shows the possible range of DEESS in the daily diagram for all the non-dominated solutions in scenario 36.

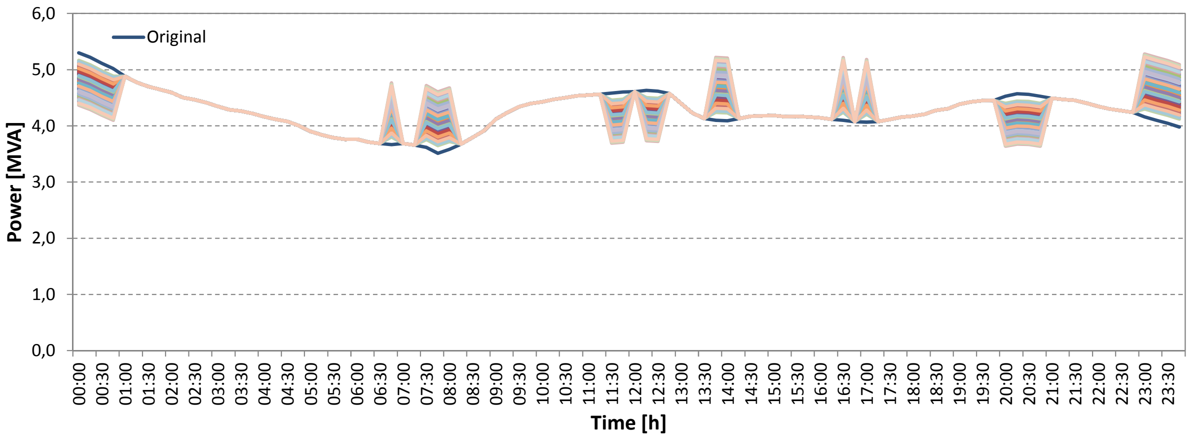

Figure 4-31 – Scenario 36 non-dominated solutions impact on the SE LD.

Even without economic attractiveness for simply buying and selling energy, results show how important DEESS may prove to be for a network, providing power services which can be paid for. An example may be the possibility of replacing at least part of the existing conventional generators which are being used simply as backup generators. However, due to the lack of regulation on this issue, an adequate framework should be developed to deploy energy storage applications.

4.6.6 Sensitivity analysis

Using the optimization process results as reference, several feed-in tariffs were simulated to verify the associated NERB and also to make a preliminary assessment of the values required for obtaining a positive net benefit of deploying DEESS. Considering non-dominated solutions associated to each MSch, the solutions with the highest NERB were selected, i.e., scenarios 15, 36 and 66 with 23, 24 and 21 batteries to install in buses, comprising MSch 1, 2 and 3, respectively.

Table 4-13 - Sensitivity analysis applied to objective function NERB

Surplus feed-in tariff		**MSch 1 - NERB**				**MSch 2 - NERB**			**MSch 3 - NERB**		
N.º	**[€]**	**Δ**	**Daily**	**Δ**	**Annual**	**Daily**	**Δ**	**Annual**	**Daily**	**Δ**	**Annual**
		[%]	**[€]**	**[%]**	**[€]**	**[€]**	**[%]**	**[€]**	**[€]**	**[%]**	**[€]**
1	28.14	0%	31.60	0%	11 565.63 €	38.58	0%	14 120.74 €	25.6	0%	9 376.40 €
2	38.14	36%	41.19	30%	15 075.93 €	53.59	39%	19 615.13 €	34.4	34%	12 581.46 €
3	48.14	71%	50.78	61%	18 586.24 €	68.61	78%	25 109.53 €	43.1	68%	15 786.53 €
4	58.14	107%	60.37	91%	22 096.54 €	83.62	117%	30 603.92 €	51.9	103%	18 991.59 €
5	68.14	142%	69.96	121%	25 606.85 €	98.63	156%	36 098.31 €	60.6	137%	22 196.65 €
6	78.14	178%	79.56	152%	29 117.16 €	113.64	195%	41 592.70 €	69.4	171%	25 401.71 €
7	88.14	213%	89.15	182%	32 627.46 €	128.65	233%	47 087.09 €	78.2	205%	28 606.77 €
8	190.86	578%	187.67	494%	68 686.59 €	282.86	633%	103 527.47 €	168.1	556%	61 530.33 €
9	132.89	372%	132.06	318%	48 335.10 €	195.83	408%	71 672.96 €	117.3	358%	42 948.53 €
10	194.56	591%	191.21	505%	69 982.82 €	288.41	648%	105 556.35 €	171.3	569%	62 713.84 €
11	187.11	565%	184.06	482%	67 367.27 €	277.22	619%	101 462.44 €	164.8	543%	60 325.73 €
12	129.13	359%	128.46	307%	47 015.78 €	190.19	393%	69 607.93 €	114.1	345%	41 743.93 €
13	190.80	578%	187.61	494%	68 663.50 €	282.76	633%	103 491.32 €	168.1	556%	61 509.24 €

Table 22 shows a sensitivity analysis on the influence of the surplus feed-in tariff on the results. Benefits may have higher relative impacts than the relative variation of the tariff. As an example, for a 36% variation of the surplus feed-in tariff, the network energy rate benefit increased by 30%, 39% and 34%, depending on the MSch being 1, 2 or 3, respectively.

The results showed the importance of market prices to ease the DEESS interest. As an example, scenarios 15 and 66 should increase by 6% and 2% in order to present a similar evolution to the tested surplus feed-in tariffs. Moreover, DEESS only presents a net positive economic result when the surplus feed-in tariff increase to 190.86€/MWh, 132.89€/MWh and 194.56€ for MSch 1, 2 and 3, respectively. Such values are approximately 5 to 7 times higher than the surplus feed-in tariff used in the year 2008.

If GHG emission reduction was considered as DEESS additional revenue measured (as presented in section 4.6.4), the surplus feed-in tariff would have to be increased to 187.11 €/MWh, 129.13 €/MWh and 190.80 €/MWh for MSch 1, 2 and 3, respectively (about 2% lower values, when compared to results without considering GHG emissions).

Even considering an hypothetical efficiency of 100%, DEESS would need a surplus feed-in tariff between 4 to 6 times higher than the one currently used for the management schemes (approximately 165.18€/MWh, 112.07€/MWh and 167.16€ for MSch 1, 2 and 3, respectively).

The results show that DEESS can only become attractive if the economic benefit results from more than just energy purchasing and selling. Future viability should also include power demand services besides energy service, taking profit of its fast response capability to network requests of power demand.

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5 Conclusions and future work

This thesis presents a methodology to provide the decision maker (DM) the relevant information needed to define his/her preferred locations of distributed energy storage devices on an electrical distribution network, taking into account both economic and technical impacts. The methodology also assists on the definition of the best schedule for the storage units operation, aiming to optimize four objective functions which are some of the main objectives of DEESS presented in the literature: the minimization of power losses, voltage deviation and investment, as well as the maximization of the revenue resulting from the difference between energy sale and energy purchase prices at different time periods. Except for power losses and voltage deviation, the chosen objectives have no interdependencies, making the use of a multiobjective genetic algorithm a suitable choice for this problem. The consequence is that, instead of being presented with an “optimal solution”, the DM will have to choose the preferred solution from the highest quality set of non-dominated solutions presented by the search tool, assuming tradeoffs between the objectives.

The research question to be answered took into consideration the circumstances in which urban DEESS would be feasible. The answer to this question strongly depends on the associated technological costs, being this feature one of the most important issues for DEESS economic viability and attractiveness. Results showed that a higher technological efficiency of DEESS devices would be very important to achieve a positive economic benefit. Even with the possible future use of a suitable feed-in-tariff, DEESS feasibility may depend of combining energy, power and environmental services for increasing its economic attractiveness.

The economic CO_2 impact assessed within the EU ETS market was not enough to obtain a positive economic benefit within the chosen case-study. The low market value of the considered emissions limited the contribution of this potential benefit to the viability of the solution. Therefore, the viability of DEESS is highly dependent of the consideration of all possible positive impacts.

The possibility of assessing power generation costs could have helped to increase the DEESS interest. However, this possibility proved to be unfeasible since the current energy market runs on daily energy auctions, the market players not being required to inform on their assumed costs when delivering the contracted energy.

The availability of DEESS depends on the envisaged management scheme since the ESS can only provide a service at a time. The energy services to be provided are restrained by the considered technology, with different performance impacts (more or less severe) and different costs (e.g. those dependent on the expected lifetime), being battery storage technologies able to provide most of the energy services to the network.

The location and sparsity of storage units strongly depends on the used management scheme. Different impact results and solutions are obtained for different management schemes, suggesting the need to incorporate also this level of decision on the multiple objective formulation. A definitive solution implies naturally the analysis of the possible tradeoffs according to the preferences of the DM, which could be any private investor, the DSO or an authority. Depending on the stakeholder, different objectives could be pursued, leading to a different final “best” choice among the non-dominated solutions.

The developed work enlightened the need to have a framework that stimulates existing or new market players to invest on ESS as a way to increase the share of renewable energy, by storing energy generated on surplus periods to be used when generation is limited. One possible approach to this objective could consist of using a feed-in-tariff scheme, rewarding energy recovered from energy storage on an equivalent basis to the energy delivered directly to the grid by renewable generators. The MSch profile definition for renewable integration should take into consideration the real behavior of the wind, in order to obtain a plausible management scheme of the DEESS, as well as, to calculate the associated benefit. Although initially unforeseen, a data clustering process enabled the use of real data prototypes of prices, load diagrams and wind generation, allowing a more accurate definition of the impacts of the use of storage devices.

In order to improve the developed methodology, future work should include the following directions:

- To incorporate a dynamic C/D optimization routine, searching for the best ESS management scheme, given the economical and technical contraints;

- To consider the deployment of distributed renewable generation within distribution networks, a future research should include the impact assessment of DEESS, when facing the non dispatchable injection of small power generation. This feature will enhance the suppletive nature of DEESS by characterizing and additional element of the complex energy market environment.
- To increase the number of objective functions in order to assess the influence of DEESS capacity on the profile diagram, and to include the assessment of regulation services such as the secondary and tertiary frequency regulation control;
- To include a second optimization procedure to define the optimal capacity of individual units per installation site. This feature may introduce some insights regarding the assessment of best location of DEESS as well as give insights on how storage capacity could influence the network global performance.

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7 Appendix

7.1 Management scheme A prototypes

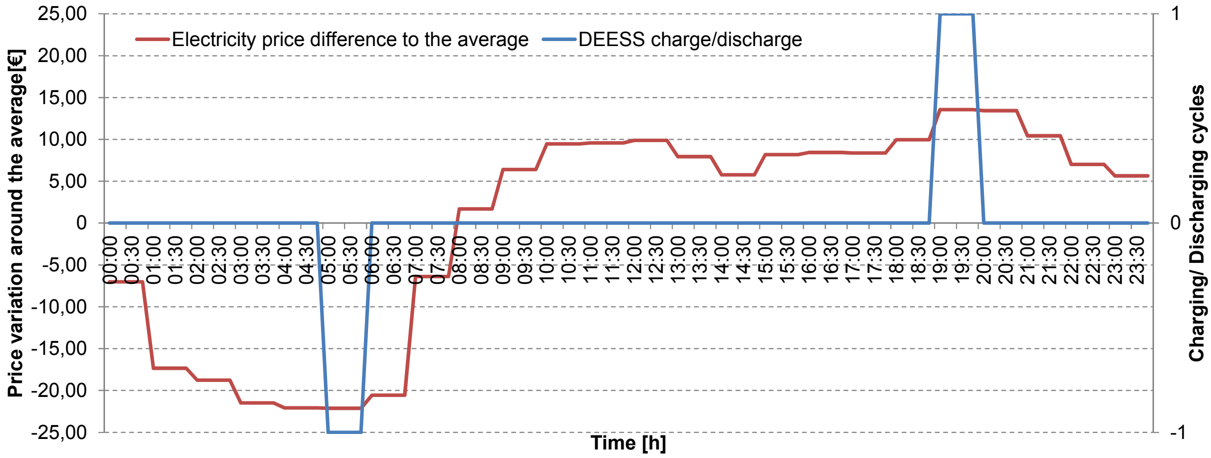

Figure 7-1 – Analysis of the energy price variation for prototype#1

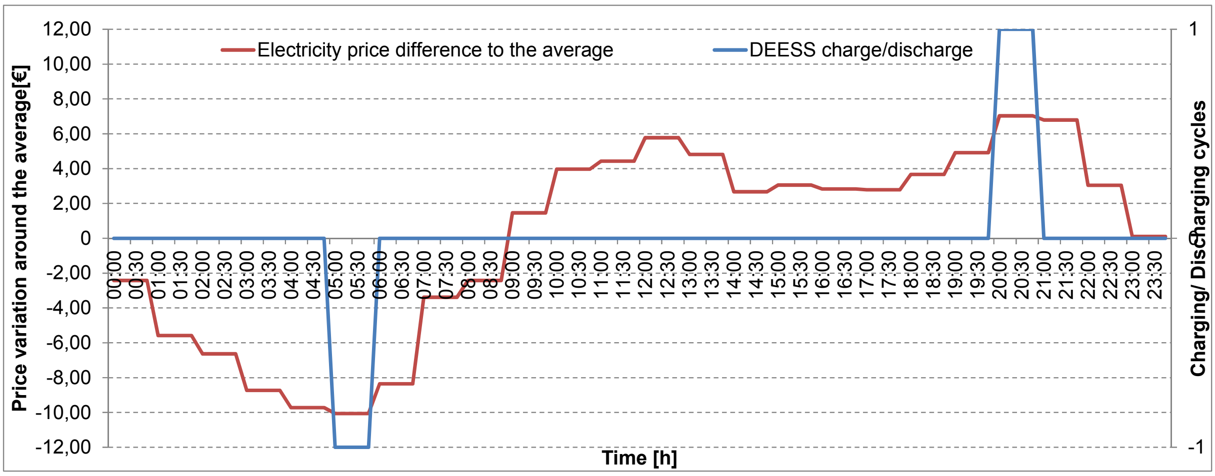

Figure 7-2 – Analysis of the energy price variation for prototype#2

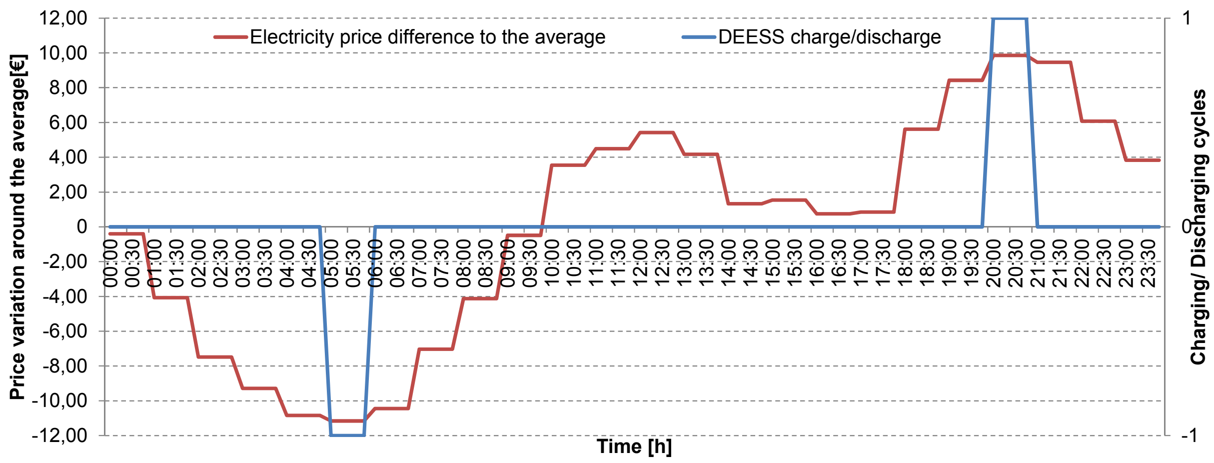

Figure 7-3 – Analysis of the energy price variation for prototype#3

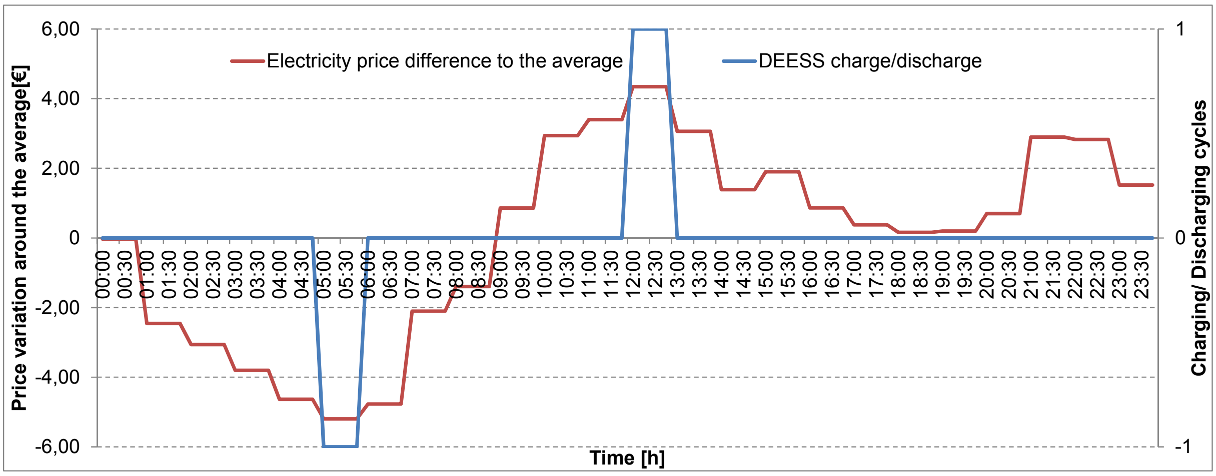

Figure 7-4 – Analysis of the energy price variation for prototype#4

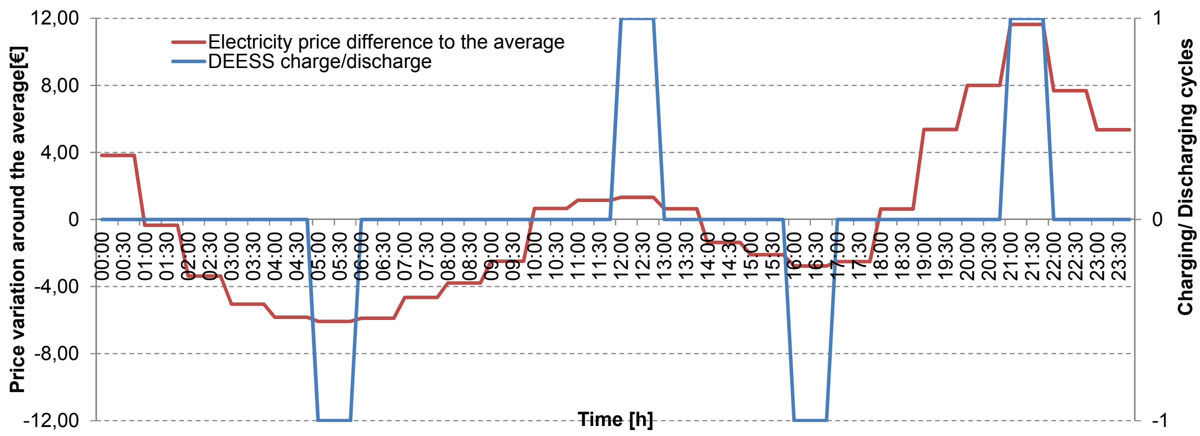

Figure 7-5 – Analysis of the energy price variation for prototype#5

7.2 Management scheme B prototypes

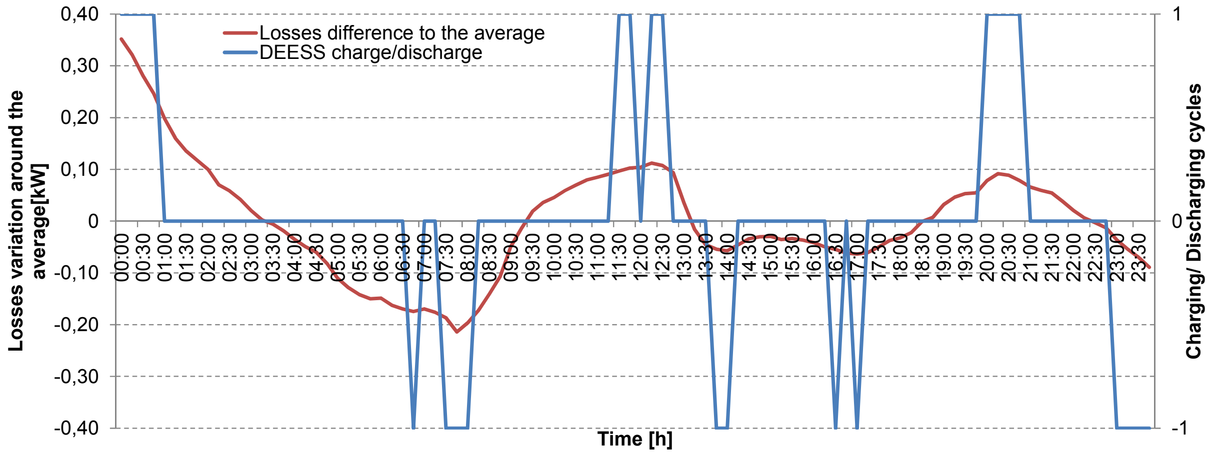

Figure 7-6 – Analysis of the variation of NEL for prototype#1

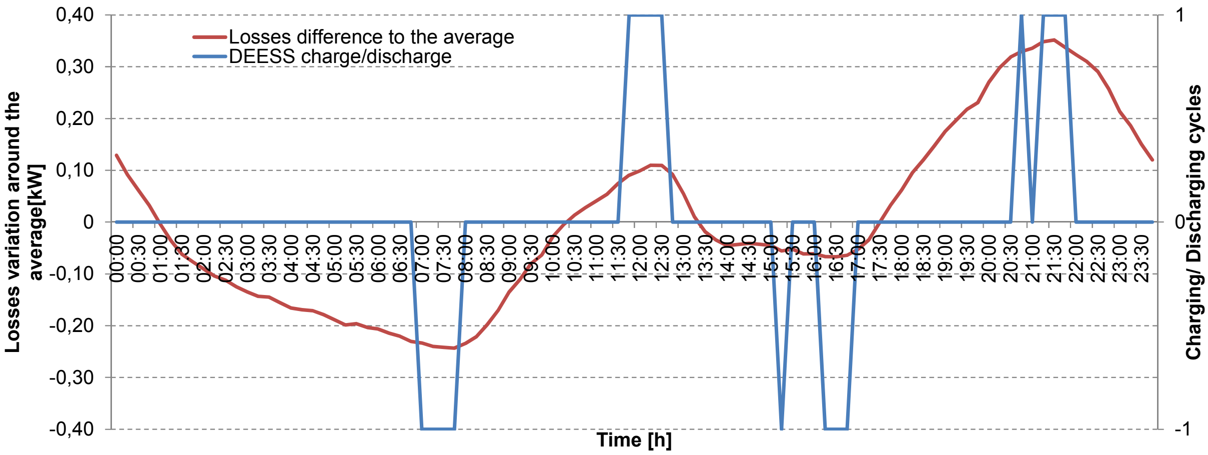

Figure 7-7 – Analysis of the variation of NEL for prototype#2

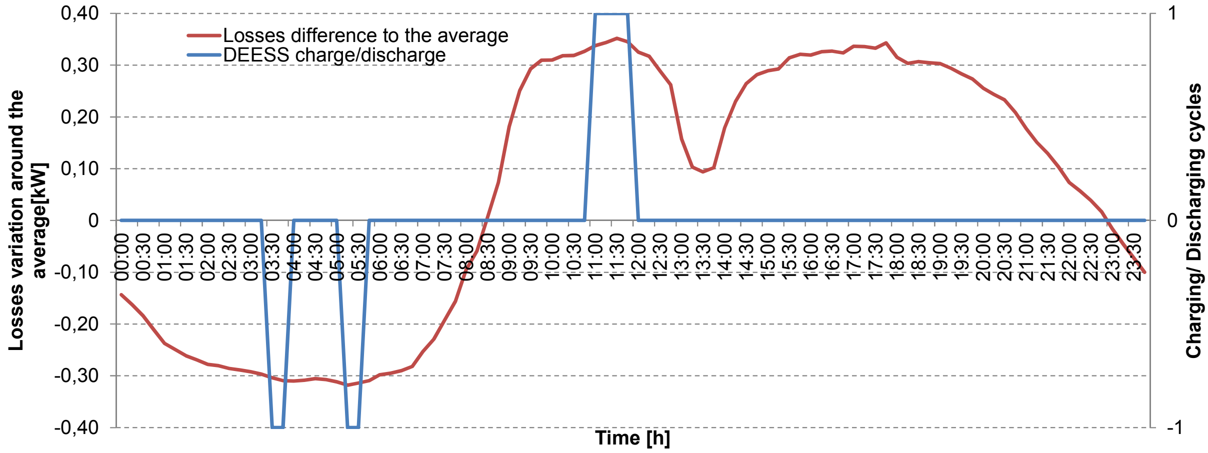

Figure 7-8 – Analysis of the variation of NEL for prototype#3

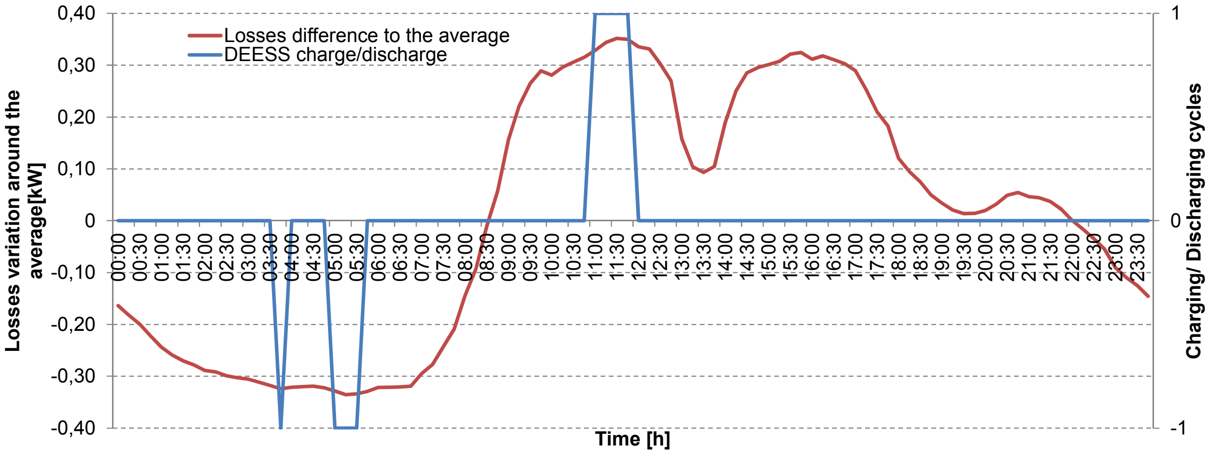

Figure 7-9 – – Analysis of the variation of NEL for prototype#4

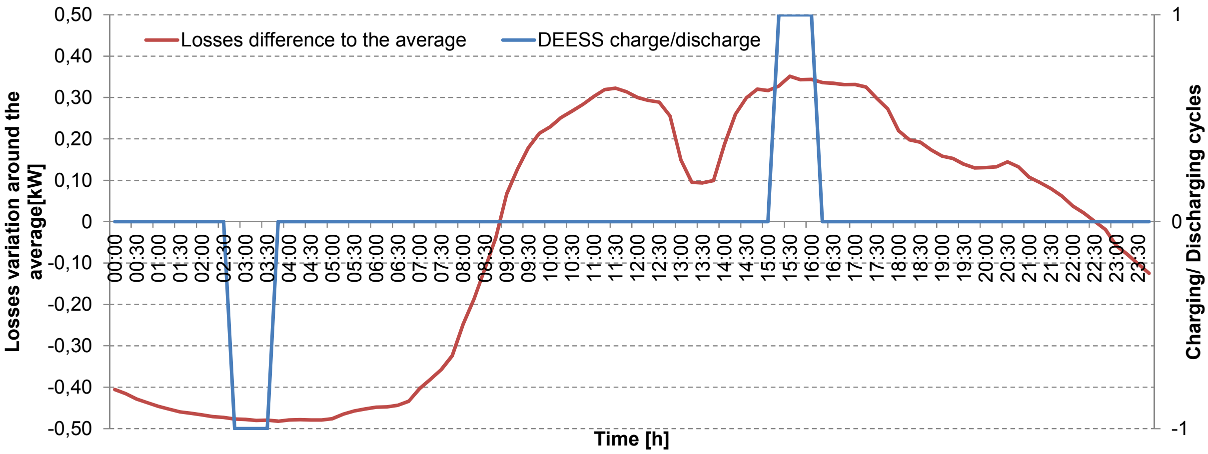

Figure 7-10 – – Analysis of the variation of NEL for prototype#5

7.3 Management scheme C prototypes

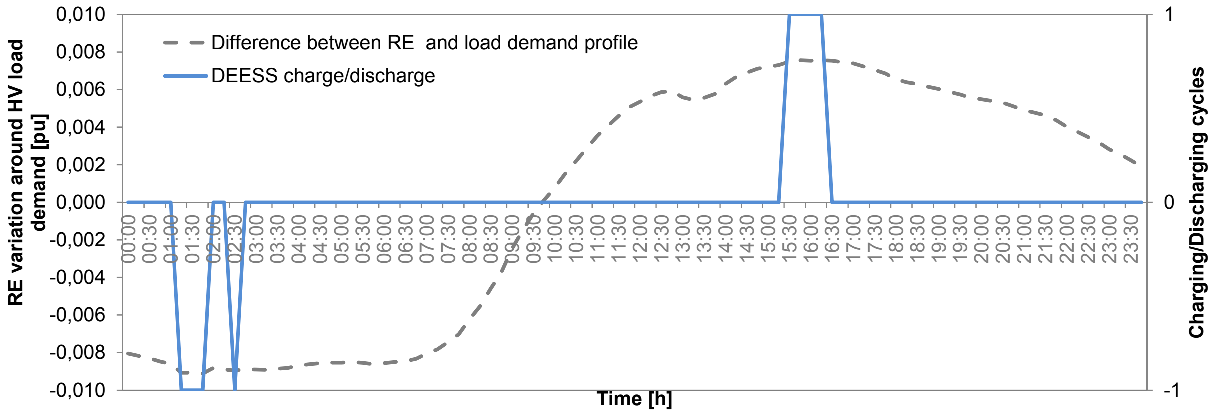

Figure 7-11 – Renewable generation variation analysis when considering the average profile of LD and renewable generation prototype#1

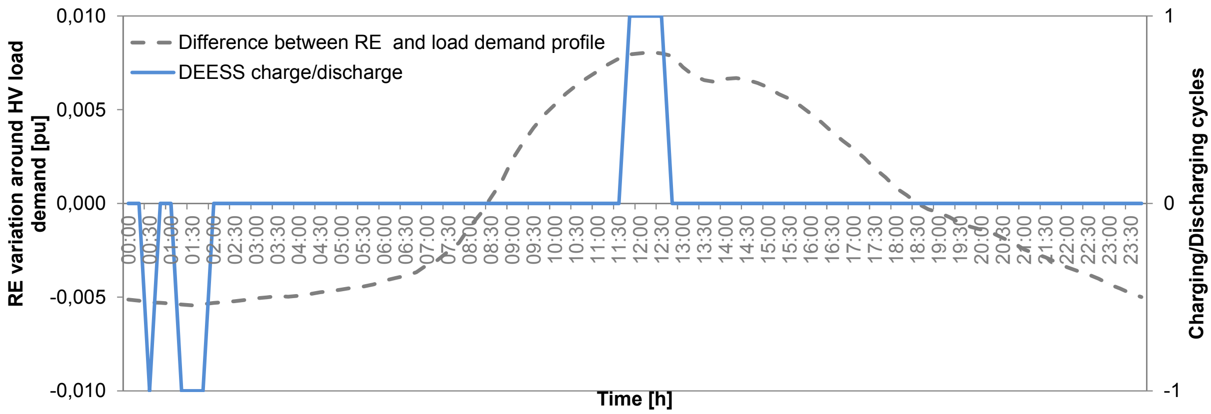

Figure 7-12 – Renewable generation variation analysis when considering the average profile of LD and renewable generation prototype#2

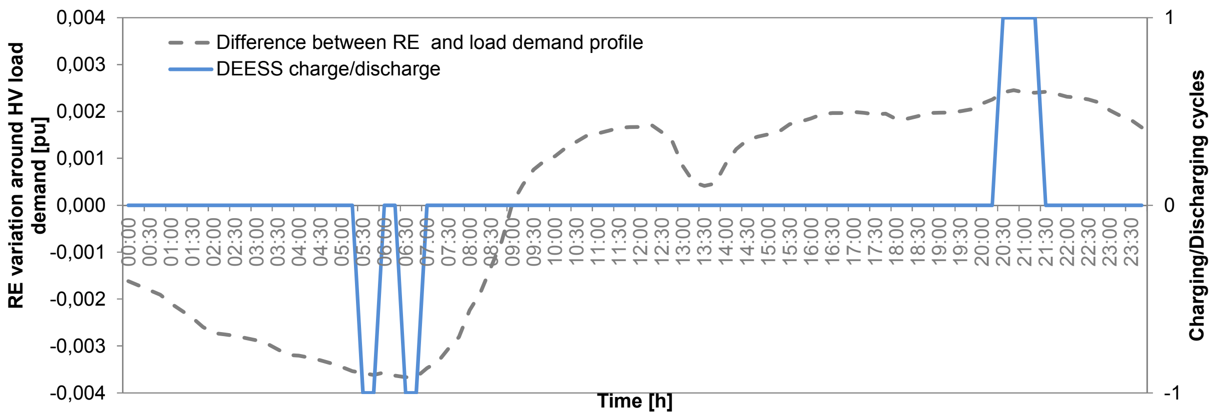

Figure 7-13 – Renewable generation variation analysis when considering the average profile of LD and renewable generation prototype#3

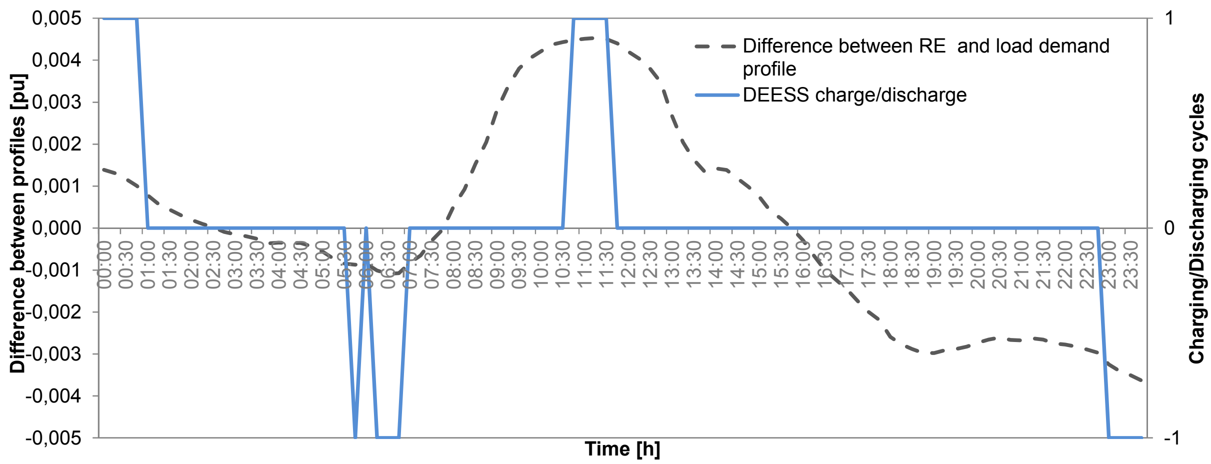

Figure 7-14 – Renewable generation variation analysis when considering the average profile of LD and renewable generation prototype#4

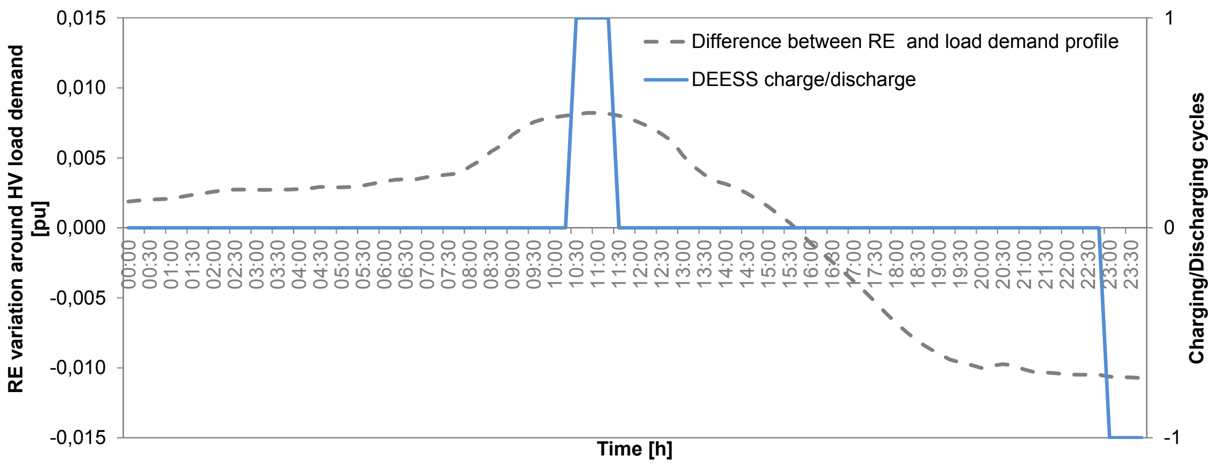

Figure 7-15 – Renewable generation variation analysis when considering the average profile of LD and renewable generation prototype#5

7.4 Summarized results for MSch A

Table 7-1 – Summarized results for MSch A

		Original		NEL [kWh/day]				NVqmd [p.u.]			NSAC [€]		NERB [€]	
Sim./ Scenario		NVqmd [p.u.]	NEL [kWh/day]	Min.	Max.	NEL Variat. range	NEL improv.	Min.	Max.	NVqmd improv.	Min.	Max.	Min.	Max.
MSch A	1	0,1012	7670,98	7671,00	7702,00	31,00	0,02	0,1010	0,1010	-0,0002	20905,00	131400,00	8,00	53,00
	2	0,1012	7670,98	7670,00	7696,00	26,00	-0,98	0,1010	0,1010	-0,0002	26877,00	131400,00	7,00	35,00
	3	0,1012	7670,98	7670,00	7696,00	26,00	-0,98	0,1010	0,1010	-0,0002	23891,00	131400,00	7,00	39,00
	4	0,1012	7670,98	7670,00	7690,00	20,00	-0,98	0,1010	0,1010	-0,0002	38823,00	116468,000	8,00	25,00
	5	0,1012	7670,98	7671,00	7725,00	54,00	0,02	0,1010	0,1010	-0,0002	26877,00	125428,00	12,00	58,00
	6	0,1012	7705,60	7698,00	7709,00	11,00	-7,60	0,1010	0,1010	-0,0002	20905,00	119455,00	8,00	48,00
	7	0,1012	7705,60	7693,00	7701,00	8,00	-12,60	0,1010	0,1010	-0,0002	14932,00	119455,00	4,00	32,00
	8	0,1012	7705,60	7693,00	7703,00	10,00	-12,60	0,1010	0,1010	-0,0002	14932,00	128414,00	4,00	38,00
	9	0,1012	7705,60	7702,00	7719,00	17,00	-3,60	0,1010	0,1010	-0,0002	32850,00	125428,00	7,00	27,00
	10	0,1012	7705,60	7696,00	7732,00	36,00	-9,60	0,1000	0,1000	-0,0012	11945,00	128414,00	5,00	59,00
	11	0,1012	8334,89	8312,00	8328,00	16,00	-22,89	0,1010	0,1010	-0,0002	11945,00	128414,00	5,00	52,00
	12	0,1012	8334,89	8316,00	8329,00	13,00	-18,89	0,1010	0,1010	-0,0002	11945,00	125428,00	3,00	33,00
	13	0,1012	8334,89	8316,00	8327,00	11,00	-18,89	0,1010	0,1010	-0,0002	14932,00	128414,00	4,00	38,00
	14	0,1012	8334,89	8312,00	8327,00	15,00	-22,89	0,1010	0,1010	-0,0002	17918,00	119455,00	4,00	26,00
	15	0,1012	8334,89	8333,00	8392,00	59,00	-1,89	0,1010	0,1180	0,0168	17918,00	131400,00	8,00	60,00
	16	0,1012	7725,51	7717,00	7728,00	11,00	-8,51	0,1010	0,1010	-0,0002	23891,00	128414,00	10,00	52,00
	17	0,1012	7725,51	7716,00	7726,00	10,00	-9,51	0,1010	0,1010	-0,0002	23891,00	122441,00	6,00	32,00
	18	0,1012	7725,51	7716,00	7725,00	9,00	-9,51	0,1010	0,1010	-0,0002	23891,00	125428,00	7,00	37,00
	19	0,1012	7725,51	7699,00	7720,00	21,00	-26,51	0,1010	0,1010	-0,0002	8959,00	125428,00	2,00	27,00
	20	0,1012	7725,51	7724,00	7786,00	62,00	-1,51	0,1010	0,1170	0,0158	8959,00	131400,00	4,00	60,00
	21	0,1012	7232,95	7201,00	7221,00	20,00	-31,95	0,1010	0,1010	-0,0002	17918,00	131400,00	7,00	53,00
	22	0,1012	7232,95	7202,00	7224,00	22,00	-30,95	0,1010	0,1010	-0,0002	14932,00	140359,00	4,00	37,00
	23	0,1012	7232,95	7202,00	7223,00	21,00	-30,95	0,1010	0,1010	-0,0002	14932,00	131400,00	4,00	39,00
	24	0,1012	7232,95	7189,00	7227,00	38,00	-43,95	0,1010	0,1010	-0,0002	5973,00	131400,00	1,00	29,00
	25	0,1012	7232,95	7228,00	7273,00	45,00	-4,95	0,1020	0,1190	0,0178	8959,00	131400,000	4,00	60,00

7.5 Summarized results for MSch B

Table 7-2 – Summarized results for MSch B

		Original		NEL [kWh/day]				NVqmd [p.u.]			NSAC [€]		NERB [€]	
Sim./ Scenario		NVqmd [p.u.]	NEL [kWh/day]	Min.	Max.	NEL Variat. range	NEL improv.	Min.	Max.	NVqmd improv.	Min.	Max.	Min.	Max.
MSch B	26	0,1012	7670,98	7665,00	7746,00	81,00	-5,98	0,0930	0,0990	-0,0022	17918,00	134387,00	9,00	64,00
	31	0,1012	7670,98	7665,00	7732,00	67,00	-5,98	0,0930	0,0990	-0,0022	17918,00	128414,00	9,00	62,00
	36	0,1012	7670,98	7664,00	7755,00	91,00	-6,98	0,0930	0,0990	-0,0022	17918,00	140359,00	10,00	76,00
	41	0,1012	7670,98	7665,00	7718,00	53,00	-5,98	0,0930	0,0990	-0,0022	17918,00	119455,00	8,00	56,00
	46	0,1012	7670,98	7664,00	7746,00	82,00	-6,98	0,0930	0,0990	-0,0022	14932,00	134387,00	8,00	74,00
	27	0,1012	7705,60	7693,00	7726,00	33,00	-12,60	0,1000	0,1000	-0,0012	11945,00	131400,00	5,00	53,00
	32	0,1012	7705,60	7693,00	7730,00	37,00	-12,60	0,1000	0,1000	-0,0012	14932,00	134387,00	5,00	49,00
	37	0,1012	7705,60	7694,00	7727,00	33,00	-11,60	0,1000	0,1000	-0,0012	23891,00	131400,00	10,00	57,00
	42	0,1012	7705,60	7693,00	7729,00	36,00	-12,60	0,1000	0,1000	-0,0012	8959,00	134387,00	3,00	47,00
	47	0,1012	7705,60	7694,00	7721,00	27,00	-11,60	0,1000	0,1000	-0,0012	17918,00	125428,00	8,00	55,00
	28	0,1012	8334,89	8309,00	8327,00	18,00	-25,89	0,1010	0,1010	-0,0002	14932,00	125428,00	6,00	47,00
	33	0,1012	8334,89	8309,00	8327,00	18,00	-25,89	0,1010	0,1010	-0,0002	11945,00	137373,00	3,00	33,00
	38	0,1012	8334,89	8309,00	8323,00	14,00	-25,89	0,1010	0,1010	-0,0002	20905,00	125428,00	5,00	32,00
	43	0,1012	8334,89	8309,00	8329,00	20,00	-25,89	0,1010	0,1010	-0,0002	14932,00	128414,00	3,00	26,00
	48	0,1012	8334,89	8309,00	8321,00	12,00	-25,89	0,1010	0,1010	-0,0002	20905,00	125428,00	4,00	25,00
	29	0,1012	7725,51	7697,00	7719,00	22,00	-28,51	0,1000	0,1000	-0,0012	8959,00	119455,00	3,00	45,00
	34	0,1012	7725,51	7697,00	7714,00	17,00	-28,51	0,1000	0,1000	-0,0012	17918,00	131400,00	4,00	32,00
	39	0,1012	7725,51	7697,00	7718,00	21,00	-28,51	0,1000	0,1000	-0,0012	11945,00	128414,00	3,00	33,00
	44	0,1012	7725,51	7697,00	7718,00	21,00	-28,51	0,1000	0,1000	-0,0012	11945,00	122441,00	2,00	25,00
	49	0,1012	7725,51	7697,00	7719,00	22,00	-28,51	0,1000	0,1000	-0,0012	11945,00	128414,00	2,00	26,00
	30	0,1012	7232,95	7181,00	7225,00	44,00	-51,95	0,1000	0,1000	-0,0012	8959,00	128414,00	3,00	46,00
	35	0,1012	7232,95	7181,00	7218,00	37,00	-51,95	0,1000	0,1000	-0,0012	17918,00	122441,00	4,00	27,00
	40	0,1012	7232,95	7181,00	7227,00	46,00	-51,95	0,1000	0,1000	-0,0012	5973,00	122441,00	1,00	27,00
	45	0,1012	7232,95	7180,00	7221,00	41,00	-52,95	0,1000	0,1000	-0,0012	11945,00	134387,00	2,00	25,00
	50	0,1012	7232,95	7181,00	7216,00	35,00	-51,95	0,1000	0,1000	-0,0012	17918,00	134387,00	3,00	23,00

7.6 Summarized results for MSch C

Table 7-3 – Summarized results for MSch C

		Original		NEL [kWh/day]				NVqmd [p.u.]			NSAC [€]		NERB [€]	
Sim./ Scenario		NVqmd [p.u.]	NEL [kWh/day]	Min.	Max.	NEL Variat. range	NEL improv.	Min.	Max.	NVqmd improv.	Min.	Max.	Min.	Max.
MSch C	51	0,1012	8431,06	8420,00	8431,00	11,00	-11,06	0,1010	0,1010	-0,0002	17918,00	125428,00	6,00	42,00
	52	0,1012	8431,06	8420,00	8431,00	11,00	-11,06	0,1010	0,1010	-0,0002	20905,00	131400,00	4,00	27,00
	53	0,1012	8431,06	8420,00	8429,00	9,00	-11,06	0,1010	0,1010	-0,0002	23891,00	122441,00	4,00	23,00
	54	0,1012	8431,06	8420,00	8429,00	9,00	-11,06	0,1010	0,1010	-0,0002	23891,00	128414,00	4,00	23,00
	55	0,1012	8431,06	8420,00	8430,00	10,00	-11,06	0,1010	0,1010	-0,0002	23891,00	125428,00	3,00	18,00
	56	0,1012	8431,06	8419,00	8429,00	10,00	-12,06	0,1010	0,1010	-0,0002	14932,00	125428,00	5,00	40,00
	57	0,1012	8431,06	8419,00	8432,00	13,00	-12,06	0,1010	0,1010	-0,0002	20905,00	137373,00	4,00	29,00
	58	0,1012	8431,06	8419,00	8427,00	8,00	-12,06	0,1010	0,1010	-0,0002	26877,00	122441,00	5,00	25,00
	59	0,1012	8431,06	8419,00	8427,00	8,00	-12,06	0,1010	0,1010	-0,0002	17918,00	122441,00	3,00	23,00
	60	0,1012	8431,06	8419,00	8429,00	10,00	-12,06	0,1010	0,1010	-0,0002	14932,00	128414,00	2,00	20,00
	61	0,1012	8431,06	8417,00	8425,00	8,00	-14,06	0,1010	0,1010	-0,0002	14932,00	122441,00	6,00	47,00
	62	0,1012	8431,06	8417,00	8428,00	11,00	-14,06	0,1010	0,1010	-0,0002	8959,00	128414,00	2,00	33,00
	63	0,1012	8431,06	8417,00	8427,00	10,00	-14,06	0,1010	0,1010	-0,0002	14932,00	131400,00	4,00	39,00
	64	0,1012	8431,06	8417,00	8426,00	9,00	-14,06	0,1010	0,1010	-0,0002	14932,00	122441,00	3,00	24,00
	65	0,1012	8431,06	8417,00	8423,00	6,00	-14,06	0,1010	0,1010	-0,0002	23891,00	116468,00	6,00	31,00
	66	0,1012	8431,06	8427,00	8476,00	49,00	-4,06	0,1010	0,1020	0,0008	17918,00	131400,00	7,00	54,00
	67	0,1012	8431,06	8427,00	8473,00	46,00	-4,06	0,1010	0,1010	-0,0002	17918,00	128414,00	6,00	46,00
	68	0,1012	8431,06	8428,00	8480,00	52,00	-3,06	0,1010	0,1020	0,0008	23891,00	134387,00	9,00	49,00
	69	0,1012	8431,06	8427,00	8484,00	57,00	-4,06	0,1010	0,1030	0,0018	14932,00	137373,00	5,00	47,00
	70	0,1012	8431,06	8428,00	8488,00	60,00	-3,06	0,1010	0,1030	0,0018	20905,00	140359,00	7,00	48,00
	71	0,1012	8431,06	8429,00	8455,00	26,00	-2,06	0,1010	0,1020	0,0008	20905,00	134387,00	3,00	21,00
	72	0,1012	8431,06	8429,00	8455,00	26,00	-2,06	0,1010	0,1020	0,0008	20905,00	131400,00	3,00	22,00
	73	0,1012	8431,06	8429,00	8454,00	25,00	-2,06	0,1010	0,1020	0,0008	23891,00	128414,00	3,00	18,00
	74	0,1012	8431,06	8429,00	8459,00	30,00	-2,06	0,1010	0,1030	0,0018	38823,00	140359,00	6,00	22,00
	75	0,1012	8431,06	8429,00	8454,00	25,00	-2,06	0,1010	0,1020	0,0008	38823,00	131400,00	4,00	15,00