DOCTORAL DISSERTATION

Metodología para el emplazamiento y control de FACTS en SEP aislados utilizando información distribuida

(A methodology for FACTS Placement and Control in Isolated Power Systems Using Distibuted Information)

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PhD Thesis:

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(A METHODOLOGY FOR FACTS DEVICES PLACEMENT AND CONTROL IN ISOLATED POWER SYSTEMS USING DISTRIBUTED INFORMATION)

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Contents

List of Figures

List of Tables

Nomenclature

λ - Loading margin

ε-CM - Epsilon-constrained method

AI - Artificial intelligence

BESS - Battery energy storage system

CPF - Continuation power flow

DE - Differential evolution

DFACTS - Distributed flexible alternating current transmission systems

DG - Distributed geneator

DSTATCOM - Distribution static compensator

DSSC - Distributed static series compensator

Ev - Eigenvalues

FACTS - Flexible alternating current transmission systems

FDM - Fuzzy decision method

FPI - Fused performance index

GA - Genetic algorithm

GHG - Greenhouse gases

GSA Gravitational search algorithm

IPFC - Interline power flow controller

LP - Load profile

MCS - Monte Carlo simulation

MI - Mutual information

MINLP - Mixed-integer non linear programming

MRI - Mean relative improvement

OPF - Optimal power flow

PDF - Probability density function

PI - Proportional integral

PF - Power flow

PMU - Phasor measurement unit

PSO - Particle swarm optimisation

PST - Phase-shifting transformers

RES - Renewable energy sources

S-AFA Self-adaptive firefly algorithm
SSSC - Static synchronous series compensator
STATCOM - Static compensator
SVC - Static VAR compensator
TCR - Thyristor-controlled reactor
TCSC - Thyristor-controlled series capacitor
TSC - Thyristor-switched capacitor
TSO - Transmission system operator
TSR - Thyristor-switched reactor
UPFC - Unified power flow controller
VSC - Voltage source converter
VSCOPF - Voltage stability constrained optimal power flow
VSI - Voltage stability index

Chapter 1

Introduction

In the last few decades, power systems within the European Union have undergone a major transformation that has changed the way in which they are managed. The shift to a management scheme based on the open-access to transmission grids has led to important transformations. In this context, multiple actors with diverse, and often conflicting, objectives interact taking advantage of market tools. At the same time, transmission systems need to ensure a reliable energy exchange between generators and customers, as well as ensuring competency between the different actors [1]. Power system management, and particularly transmission expansion planning, need to consider the interactions between multiple agents. Furthermore, they must provide a fair access to the transmission grid for all actors while ensuring quality of supply and system efficiency.

Recently, power systems have experienced a noticeable increase of generators based on renewable energy sources (RES). Since the 1960's concern about climate change has drawn more and more interest in developed societies. This has led to important changes in power systems, in which RES has become a significant part of the generation mix. For instance, in the European Union, the share of renewable power has increased from 14.3 % to 30.7% between 2004 and 2017 [13]. These kinds of technology do not cause greenhouse gases (GHG) emissions and are, sometimes, cheaper than conventional generation units. Nevertheless, their random nature makes them unmanageable, so they may harm power systems stability. The increasing presence of renewable unmanageable generators entail new challenges related to electric power generation requirements [14]. The transition towards power systems with a greater share of RES will increase their complexity. Transmission systems operators (TSOs) may need to modify their analysis tools and procedures in order to consider the influence of these technologies [15]. The uncertainty introduced by the RES and the need for new transmission infrastructures to accommodate new unmanageable generators are integration issues that remain unsolved [3].

Small isolated power systems display issues related to high RES penetration nowadays. Such power systems present inherent characteristics that make them particularly vulnerable to instability issues. On the one hand, conventional generation units tend to have restrictive operating characteristics that do not allow large power variations such as those of RES. On the other hand, isolated power systems tend to have low meshed transmission grids, which may increase the impact of RES power variations [16]. When instability issues occur, TSOs may command some renewable generators to disconnect so as to ensure power systems stability [17]. Similarly, they may allow them to re-connect when stability is recovered. While continental power systems are taking advantage of increased amounts of RES power, reducing GHG emissions and generation costs, small isolated power systems are beginning to display the limits of RES power integration.

The increase of renewable generation and the liberalisation of power systems have entailed changes in analysis tools used by TSOs. New generation units, mainly based on RES, greatly influence transmission system expansion planning. For this reason, traditional planning processes have been modified to include renewable generators and their interactions with demand [3]. In this context, new analysis tools that take into account a greater amount of demand and renewable generation scenarios are needed, particularly in small isolated power systems.

Power systems will have to guarantee security of supply, while, at the same, time they may achieve low electricity prices and allow a high share of RES with the least environmental impact possible [2]. A modest increase in electrical demand is expected in the coming years, while millions of customers may be allowed to exchange their own electricity locally, through the grid [18]. This will create new challenges in power systems operation, such as line congestions or power oscillations, which may become more frequent and severe. Nonetheless, transmission expansion planning is being delayed, or even frustrated, by legal and administrative issues [19]. These difficulties are usually related to land use and the environmental impact of new infrastructures.

In the 1980's the first flexible alternating current transmission systems (FACTS) were developed. FACTS devices are based on power electronics and are designed to provide control of one or more power systems parameters in a flexible manner [20]. In doing so, it is possible to manage power flows and, consequently, enhance power systems stability. FACTS devices have proven to be highly effective for voltage control, power flow management, harmonic suppression, oscillations damping, load balancing, etc. [10]. In this research, we will focus on the capability of FACTS devices to provide voltage control, particularly from a steady-state perspective.

1.1 Problem Definition

FACTS devices are mainly based on reactive power compensation, the effect of which is inherently local, given that it attenuates as distance increases. Due to the great investments needed to implement these solutions, they need to be properly placed and operated. This is why the optimal placement and configuration of FACTS devices are important for voltage control appliances. Several research projects have demonstrated that FACTS devices impact assessment is a complex problem. For instance, it has been found that the weakest bus in terms of voltage stability may not be the best location for FACTS devices, and that multiple variables need to be considered [21]. In this research, we will focus on how load variations influence these problems.

FACTS devices impact assessment studies are frequently oriented to find their best placement, type and size [10]. Alternatively, researches have proposed different FACTS devices controllers tuning techniques so as to achieve an adequate dynamic behaviour ([22], [23] and [24]). Nevertheless, it is also necessary to adequately select the controller's reference value. For voltage control reference value selection, based on steady-state analysis, techniques used for FACTS devices placement and sizing may be applied.

Both reference value selection and FACTS devices placement and sizing are complex multi-objective optimisation problems that involve several variables with non-linear relationships between them. These problems frequently seek to achieve different objectives simultaneously, which are usually related to voltage stability and transmission efficiency [10], so they may be treated as multi-objective optimisation problems. Given this perspective, these problems have been traditionally formulated as [25]:

1. A single-objective optimisation whose objective function is formed by the weighted sum of different individual objectives.

2. A single-objective optimisation based on the goal programming method.

3. The selection of a compromise solution, taken from a set of viable solutions considering different objectives.

Several techniques have been used to solve these problems. Classical optimisation methods were first used for this purpose due to their simplicity. These methods provide relatively good results, but they become complex when implementing various objective functions since they were not designed to deal with multi-objetive optimisation [10]. Furthermore, these methods provide results that are conditioned by the assumptions made to aggregate the different objective functions into a single one.

Recently, different techniques based on artificial intelligence (AI) have been developed and used to solve FACTS devices impact assessment problems. These techniques have attracted great interest due to their efficiency and accuracy. In partucluar, two techniques have been widely used. On the one hand, particle swarm optimisation and, on the other hand, genetic algorithms have been used in a myriad of research studies for FACTS devices impact assessment. Additionally, hybrid solutions combining different AI-based techniques or AI techniques and classical techniques have been proposed.

An alternative multi-objective method is the one based on Pareto optimality. This method is based on the selection of a set of solutions for which none of the different objectives may be enhanced without harming any of the others (non-dominated solutions). Therefore, Pareto method provides a set of compromise solutions between the different objectives.

1.2 Objective

The objective of this research is to propose a methodology for FACTS devices impact assessment that considers demand variations both in terms of total demanded power and its distribution on system buses. With this aim, different indices that measure power system behaviour have been studied and compared. An index selection method, based on the information they provide, is also proposed. The proposed methodology has been used for FACTS devices placement and voltage control reference value selection.

FACTS devices impact assessment has been analysed by various authors using different optimisation techniques and objective functions. Nonetheless, only a small number of them include demand variations in their analysis. In fact, most of research studies are focused on one or a handful of demand scenarios [10]. Similarly, TSOs tend to utilise the ”peak/valley” approach in their studies, which in the end, entails the same limitations. Given the transformations that power systems have experienced, it is necessary to develop FACTS devices impact assessment analysis tools that take into account demand variations. More precisely, variations of total demanded power and demand distribution need to be considered.

1.3 Research Questions

FACTS devices impact on power systems depends on numerous variables. In particular, it has been demonstrated that results of these studies may be significantly influenced by interactions between renewable generation and load variations [26]. The authors have demonstrated that, in the presence of renewable generators, peak scenario may not be the best option for FACTS devices impact assessment, as it may not ensure an optimal solution. Therefore, the number and configuration of demand scenarios becomes relevant to ensure a robust result in such analysis.

Research studies in which a significant number of scenarios are included commonly use one of the following techniques: Monte Carlo simulation (MCS), load profiles (LP) and historical data. Nevertheless, we where unable to find a method in the literature that allows us to adequately represent power system demand in a disaggregated manner. On the one hand, it is necessary to consider demand from different substations as dependent variables whose dependency is not deterministic. On the other hand, modeling techniques may allow us to represent future demand. The revised methods do not guarantee these two conditions at a reasonable level of complexity.

It is worth keeping in mind that load variations, especially those related to load share, may affect FACTS devices assessment results. In this research, a methodology for FACTS devices impact assessment that takes demand variations into account is proposed. This methodology has been used for FACTS devices placement, based on historical distributed data, under the following hypothesis:

- **Hypothesis 1:** Considering a greater number of demand scenarios with a variable load share among the different buses may provide better results in FACTS devices placement studies.

In this context, load share is understood to be the distribution of the aggregated power system load into the different system buses or substations.

It is also important to highlight that voltage control is inherently local. This obliges power systems planners to adequately place FACTS devices and to take care of their configuration. Nevertheless, FACTS devices steady-state configuration has not been sufficiently studied in accordance with the literature review.

As a part of FACTS devices impact assessment on power systems, voltage control reference value selection may be influenced by multiple variables. In particular, load variations may significantly influence the results of such studies. For this reason, we consider that it is important to take into account an adequate number of demand scenarios so as to properly model it.

In this research, the proposed methodology has also been used for voltage control reference value selection in FACTS devices applications. To this end, historical distributed demand data has been used to account for demand variations. This approach is based on the following hypotheses:

- **Hypothesis 2:** The reference value influences the effectiveness of the voltage control performed by FACTS devices.

- **Hypothesis 3:** Considering a greater number of demand scenarios with a variable load share among the different buses may provide better results in FACTS devices configuration studies.

1.4 Structure of the Document

The remaining part of this document is organised as follows: after the contextualization of the research carried out in this chapter, a revision of the existing literature related to the main research topics is presented in chapter 2. Firstly, a description of how recent changes have affected power systems operation and planning is provided. Then a comparative analysis of the main types of voltage stability indices is presented. Finally, a review of the main FACTS devices, their applications and the methods and approaches used for assessing their impact is provided. The implications of the augment of renewable unmanageable generation has also been discussed. Additionally, the main aspects of this review have been specified to small, isolated power systems.

In chapter 3, a revision of the main issues regarding demand scenarios creation is presented. The main techniques used for this purpose are also discussed. The objective of this review is to portray how the needs for demand scenarios creation have evolved in the context described in chapter 2. Furthermore, the advantages and drawbacks of the main existing methods are discussed.

In chapter 4, the main research hypotheses are described. Based on the research questions, and taking advantage of the main conclusions of the literature review, the hypotheses are presented and developed. The theoretical proof of load share's influence on FACTS devices placement is presented. Additionally, the premises on which this research is based, regarding FACTS devices placement and control methods, are provided.

Subsequently, the proposed solution to FACTS devices placement is presented in chapter 5. The experimental work carried out to test the hypotheses is described in chapter 6. In this chapter, experiments are described and results are presented.

Finally, in chapter 7, the main conclusions and contributions of this research are presented and discussed. The discussion of these conclusions has provided interesting reflections on FACTS devices impact assessment. At the same time, some promising considerations have emerged, which may be the basis of future research.

Chapter 2

State of the Art

Electrical power systems are mainly composed of synchronous generators and electrical loads, which are connected by transmission elements. Given that generators tend to be placed far away from consumption areas, power has to be transmitted over significant distances [4]. For this reason, power delivery systems have been divided into transmission and distribution systems.

Transmission systems cover large distances at high voltages, usually between 60 and 500 kV. On the other hand, distribution systems span the vicinity of consumption areas at voltage levels that range from 100 V to a few tens of kV [14]. Another important difference between transmission and distribution grids is related to their topology (how their lines are connected). Transmission grids have a network configuration, since every node is usually fed by more than one line. Distribution grids are, in contrast, radial, since lines span sequentially and power reaches every node by only one path [14]. This has different implications in their operation. Basically, meshed power grids are more efficient and reliable, since alternative paths exist for electrical transmission.

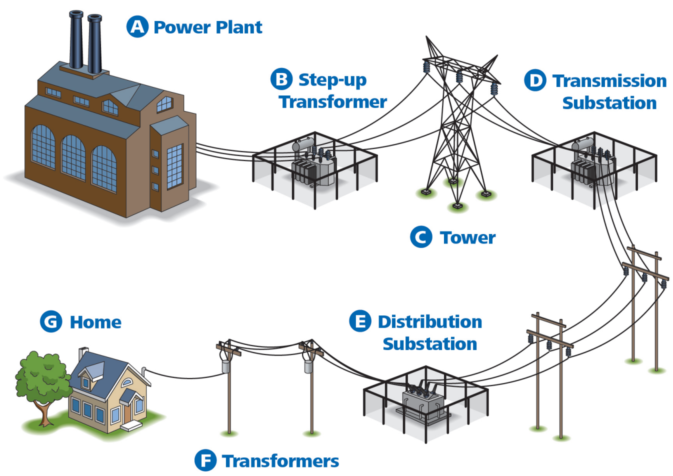

Figure 2.1: Power systems composition.

In recent decades, European power systems have undergone a major transformation in order to introduce electricity markets. In contrast to the traditional vertically integrated scheme, this new paradigm assumes that optimal allocation of generation resources is better achieved through market mechanisms [14]. A common feature of restructured power systems is the unbinding of generation and transmission. At the same time, generation and retailing activities are opened for private investment, leading to a great number of agents in the system. This new paradigm has led to major transformations and challenges in all aspects of generation, transmission and system operation [1].

Under this open-access scheme, transmission systems need to be managed so as to guarantee that all eligible market participants may use them. Thus, new transmission systems' functions emerge. Apart from linking generation and load and guarantee system reliability, transmission systems need to enable more generators to compete in a large aggregated market [1]. Therefore, they also behave as market facilitators, in charge of ensuring fair access to the facilities where the exchange of energy takes place. Consequently, the main aims of power systems expansion planning and operation are: ensuring the security of supply at the lowest cost, facilitating the integration of renewable energy sources, developing cross-border connections and facilitating market functioning [2].

2.1 Power System Operation and Planning

Power systems need to react to changes in demand and unmanageable generation so as to keep on working. In addition, unexpected issues, such as short circuits or line outages, may seriously endanger system operation. Given the complexity of power systems, many different actions need to be carried out to ensure their ability to respond adequately to these issues. Power systems management may be divided into three main activities: real-time operation, scheduling and transmission expansion planning [14].

In order to operate power systems in a safe manner, real-time actions need to be taken. The goal of real-time operation is to perform control actions to keep power systems functioning in a safe manner [14]. Operating conditions may change significantly in the course of a given day, specially in regard to demand and renewable generation. Therefore, it is necessary to plan the actions needed to ensure an adequate real-time operation. This activity is referred to as scheduling, and it is also intended to guarantee an efficient power system operation.

The availability of resources, such as generation units, transmission lines, loads, etc., impose limits on the scheduling and real-time operation actions that TSOs may take. Planning tasks seek to estimate load growth in future years and accommodate it with appropriate upgrades in transmission infrastructures and generation units. Therefore, power system planning may be basically divided into generation expansion and transmission expansion planning. Nevertheless, as will be shown, these activities influence each other and are strongly related, particularly in restructured power systems [27].

FACTS devices have become a suitable solution for reactive power management and voltage control in certain situations. Therefore, they may be included as an alternative to traditional solutions in transmission systems expansion assessment. This research aims to develop a methodology for FACTS devices impact assessment, which may be used for transmission expansion planning. Therefore, an overview of transmission expansion planning activities is provided below. A distinction between the traditional and the market-oriented approach, used in restructured power systems, is made. We will focus on the new requirements that this transformation, in addition on the increase of renewable generation, impose to transmission expansion planning. In this review, some comments on the specific case of small isolated power systems will be made.

2.1.1 Transmission Expansion Planning

European power systems have frequently been created and managed as vertically integrated industries, in which operation and planning are performed within the same utility. In this context, demand is supposed to be served by means of the minimum investment, which is usually justified by the future reliability requirements. This evaluation is performed on the basis of load and generation forecasts and under different contingencies.The final decision is made according to peak operating conditions and the time constraints of every investment option [28].

In figure 2.2 a flow chart of traditional transmission system expansion is shown. First of all, generation planning is performed to select the lowest-cost generation upgrades, and then transmission expansion planning is carried out. Transmission expansion may be formulated as an optimization problem in which cost minimization is the objective and reliability is a constraint [1].

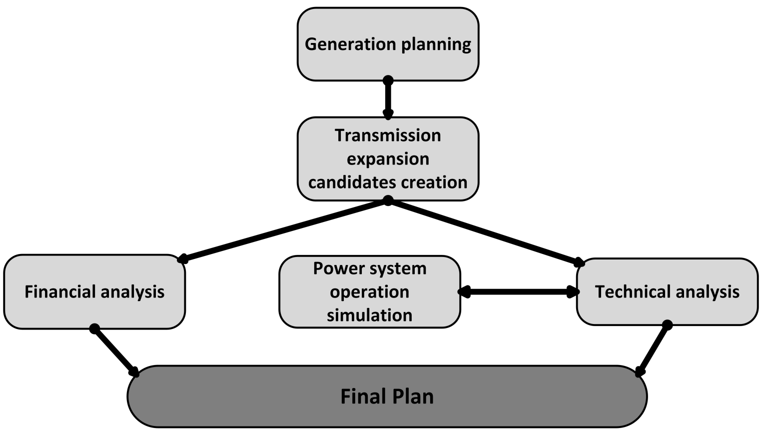

Figure 2.2: Transmission system expansion planning process in vertically integrated power system schemes [1].

The conventional approach to transmission expansion planning, so as to keep the optimisation problem tractable, is to decompose it into three main steps:

- **Generate alternative candidate solutions:** the candidate solutions for further detailed analysis may be selected by heuristic methods, analytical methods, or both.

- **Conduct detailed financial and other analyses:** economic viability of the solutions needs to be assessed. The allowed rate-of-return on capital is typically used to evaluate the investment's financial suitability.

- **Perform technical impact analysis:** power systems are required to withstand contingencies or disturbances that may occur. Steady-stated studies, based on power flow analysis, are carried out for this purpose. Later on, the most sever disturbances are studied by performing transient stability analysis.

Anticipating demand and determining appropriate expansion actions so as to satisfy load growth becomes difficult and controversial in the restructured environment. Theoretically, a competitive market should provide incentives for both short-term production and long-term investment, including generation and power delivery. How such investment signals will behave in practice and whether the results will match society's expectations or not is still unclear [14].

The deregulation of generation, transmission and distribution activities has led to multiple parties in the business. Unlike the integrated utilities in regulated schemes, the several generation enterprises have different, and sometimes conflicting, objectives. Therefore, the optimal expansion planning of restructured power systems becomes a complex problem, since competitive electricity markets represent a challenging supply chain [29].

The variety of strategies of different agents has invalidated some of the assumptions on which traditional transmission planning was based. For instance, since the paradigm of the lowest-cost expansion is not valid in a market environment, different criteria may be used for decision-making [28]. At the same time, generation expansion decisions made by enterprises are inherently affected by transmission expansion and vice versa. In such an environment, transmission expansion planning needs to rely on a governance framework that facilitates the coordination of generation and transmission investments. Additionally, short and long run social costs, changes in reliability and market power need to be considered [27].

As for traditional vertically structured power systems, the impact of new facilities has to be assessed using both technical and economic criteria. Moreover, the alternatives provided by generation planning and demand-side management have to be taken into account (see figure 2.2). In a restructured environment, however, financial analysis requires the simulation of future power system operation for which information about generation expansion is not completely available. Therefore, the process of generating candidate solutions for transmission expansion has to recognize the uncertainty due to generation expansion and load growth [1].

In a restructured environment, the incentives that drive transmission expansion decisions depend on the business models present in a given power system. In particular, transmission system business model reflects the relationship among the three business functions related to transmission services: system operation, market operation and grid ownership. The relationship between

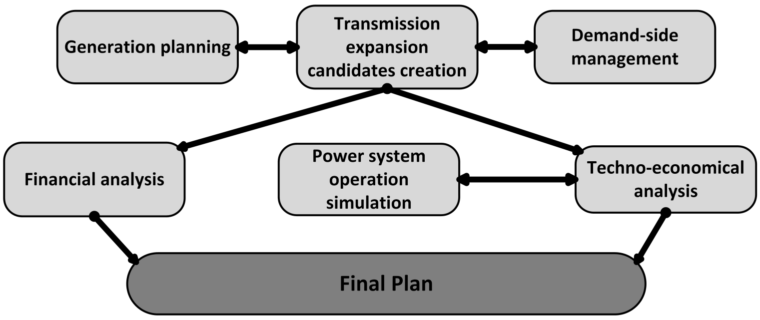

Figure 2.3: Transmission system expansion planning process in restructured power systems [1].

system operation and market operation models does not have a significant influence on transmission investment [1]. According to the authors, transmission expansion tasks in restructured power systems may be divided in two categories:

- **Transmission planning:** this includes the traditional technical, economical and environmental impact assessment. Economic impact assessment regarding all participants in the restructured power system becomes necessary. The assessment should include different perspectives and provide individual analysis for market participants, oversight bodies and public interest agencies.

  Traditional techniques for impact assessment remain valid for restructured environments. Notwithstanding, some issues have emerged due to the implications of this new paradigm. Economic assessment is not restricted to congestion reduction anymore. Market facilitation and market power limitation are now to be taken into account as a means for economic benefit. From an engineering perspective, detailed models require large amounts of data that, in most cases, are uncertain at best.

- **Transmission investment:** this takes into account the candidates for transmission expansion and their related financial analysis. The relationship between costs and revenues is crucial for investment decision making. There are four basic investment schemes: public investment, regulated private investment, market-driven investment and hybrid schemes. Most of the investment recovery schemes for transmission expansion are based on costs, rather than value, of transmission investment. Nonetheless, it is difficult to evaluate the share of usage or benefit obtained from a transmission facility. Therefore, the debate about whether cost allocation should be based on usage or benefit is likely to continue.

In recent decades, the European Union and its member states have undertaken a process of restructuring and unifying their power systems within a market-oriented scope. Under this scope, competition has been introduced into electric power generation, and market mechanisms have been implemented so as to match demand and generation. Transmission expansion planning has also been restructured, mainly under a regulated investment scheme.

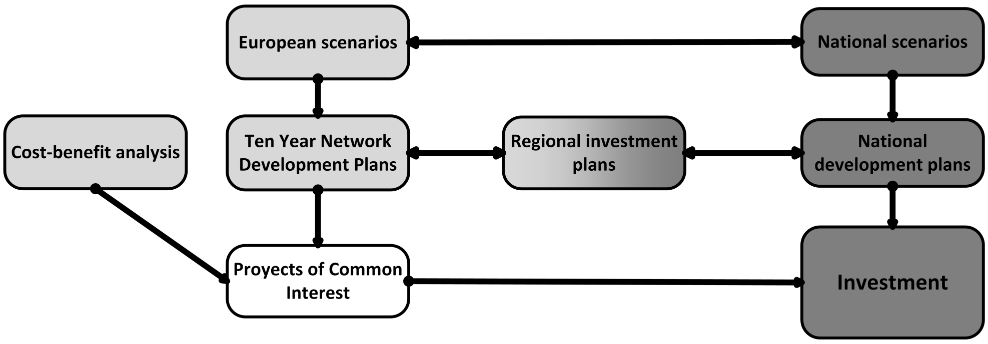

Figure 2.4: Process of infrastructure development in Europe [2].

The process of transmission expansion planning in the European Union can be observed in figure 2.4. In the figure, dark-grey boxes represent tasks that are performed by the national regulatory authorities. On the other hand, light-grey boxes represent those tasks performed by the European Network of Transmission System Operators for Electricity. The European Network of Transmission System Operators for Electricity publishes the Scenario Outlook and Adequacy Forecast report, which establishes the European reference scenarios. From this report, the Ten Year Network Development Plan is elaborated. Lately, TSOs from each member state base their network development plans on national scenarios created from the European scenarios. These plans are discussed at a regional level. Once the development plans are approved by national regulatory authorities, TSOs are in charge of undertaking the required investments. Nonetheless, the European Union has its own tools for promoting these investments, such as the Projects of Common Interest which involve both the European Commission and the member states [2].

Along with the shift to a market-oriented management scheme, the expansion of renewable unmanageable generation has forced additional changes to transmission expansion planning. Since the traditional planning techniques did not take into account these generators, they have been modified to include renewable energy supply. Given its stochastic nature, renewable generation has been introduced in the planning techniques by subtracting its power from demanded power to from the *Net Load*. Additionally, the transmission expansion assessment process has been modified to account for the interactions between demand and renewable generation [3]. In figure 2.5 a comparison between the traditional and the modified planning processes is presented.

In sum, power systems are involved in an ongoing transformation towards a great integration of renewable generation and an open-access management scheme. This transformation adds new complexities to power system analysis and, in particular, to power system expansion planning. Decision-makers need to evaluate interactions between different agents and variables. Therefore, new power systems analysis tools are needed to enable them to consider a greater number of scenarios. In particular, interactions between demand and renewable generation need to be considered.

Nonetheless, the shift to this new paradigm is already not fully accomplished, and the tradi-

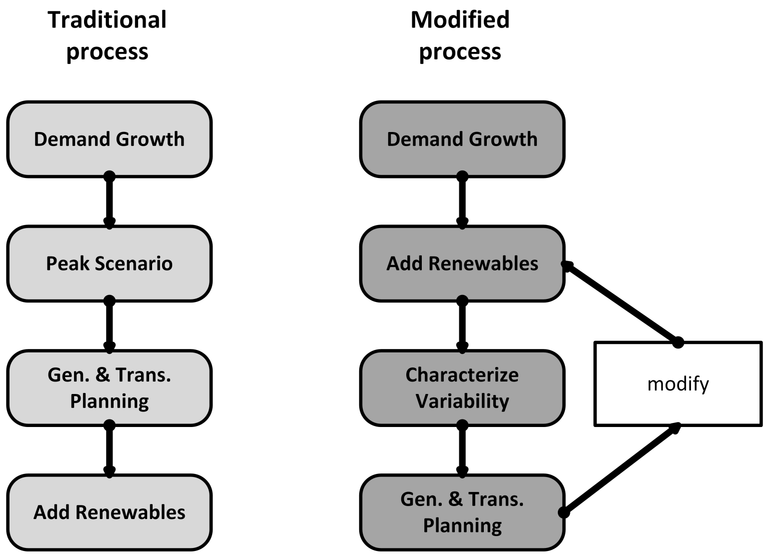

Figure 2.5: Comparison between traditional and modified planning processes [3].

tional management scheme may remain useful in power systems where competency may not be ensured. This is the case of small isolated power systems, where the transition from a vertically integrated industry to a competitive environment becomes a challenging task. On the one hand, once the main transmission and generation facilities are build and owned, it is difficult for new agents to get hold of a relevant part of the market. On the other hand, the arrival of competitors is usually complicated by land scarcity and different regulatory and environmental issues. Consequently, the traditional approach to power systems operation and analysis may endure in such territories.

Nevertheless, the present situation and perspectives of small, isolated power systems also makes it necessary to have enhanced analysis tools. The amount of RES power in these systems is usually large, given the higher costs of conventional generation in such territories and the usual availability of such resources. Furthermore, as it will be discussed in section 2.2, these power systems suffer from different instability issues, which may worsen if the share of unmanageable power rises. Thus, transmission system expansion planning needs to be particularly precise in these environments. Consequently, the need for power systems analysis tools that account for a greater number of scenarios is also justified in this context.

2.1.2 Voltage Control and Reactive Power Management

For efficient and secure operation of power systems, voltages must remain within a certain range of values. Nonetheless, this is a complex task, given that a vast number of loads that are usually fed by a great number generators. Furthermore, as load varies, the requirements of reactive power to maintain voltage levels vary. The proper selection and coordination of equipment to control voltage, by means of reactive power, is a major engineering challenge for power system operators [4].

From the perspective of power systems operation, and particularly in relation to voltage control, as power systems expand, reactive power compensation becomes more and more necessary in order to ensure adequate voltage levels and transmission capacity. Voltage control and reactive power management have been a major concern for TSOs. Due to rising variability caused by non-manageable generators and the restrictions imposed on power systems, these have been operated more and more under stressful conditions. In fact, the increasing presence of generators based on RES entails a need of more abundant and sophisticated reactive power sources [30].

Voltage control is usually structured as a centralized control. In this schemes, information from network elements is provided to the central coordinator through a communication network. Data is used by the network management system to analyse power system stability. Finally, the central coordinator makes control decisions based on this analysis [31]. Thus, TSOs monitor power systems and perform analysis so as to determine voltage and reactive power setpoints that generating units and other reactive power sources should comply with. The specific objectives of reactive power management methods are:

- To minimise active and reactive power losses, avoiding reactive power recirculation by approaching reactive power generation to where it is needed.

- To guarantee voltage control coordinating reactive power generation resources from both distribution and transmission systems.

- To operate generating units at a power factor close to unity so as to ensure reactive power reserves.

In the restructured environment, given the existence of energy markets, reactive power supply for voltage control is provided by generation units under the coordination and supervision of TSOs. TSOs take into account demand and RES forecast, as well as system loading and voltage measurements in order to provide a coordinated voltage control for a secure power system operation. Frequently, apart from generating units, power system agents have their own sources of reactive power, such as: synchronous generators, synchronous condensers, shunt capacitors or reactors, static voltage compensators (SVCs) or FACTS. As a consequence, TSOs need to negotiate the provision of reactive power for voltage control with third parties.

The Western Electric Coordinating Council (WECC) established the voltage stability criteria in terms of active and reactive power margins [32]. The reactive power margin is usually calculated using V-Q curves [33]. In doing so, reactive power required for maintaining a certain voltage value at every node is calculated. In order to guarantee a safe operation, the reactive power margin must be calculated for the worst 'N-1' contingency.

The conventional way of facing this problem is by performing consecutive power flow calculations. This, added to engineers' expertise and experience, has allowed satisfactory operation for decades. In [34] a methodology for reactive power rescheduling for voltage stability enhancement is proposed. This methodology is based on modal participation factors and OPF calculations. Voltage stability margin is calculated from the eigenvalues of the reduced Jacobian matrix, and it is maximized by rescheduling reactive power provision. Reactive power rescheduling is performed after active power economical dispatch is terminated. Nonetheless, security constraints are not included in OPF formulation. Consequently, voltage stability margin may not represent real power systems' conditions under stress situations.

In [35], a planning tool based on a Dynamic Security Constrained Optimal Power Flow is presented. The goal of this planning tool is to identify the best control actions to ensure the voltage stability of a certain operating condition. The OPF is solved twice, the first time, a restriction on voltage profile is imposed, the second time, a restriction on voltage stability margin is imposed. In [36] authors propose three OPF formulations so as to enhance operating costs as well as voltage stability in a restructured environment. Operating costs include the cost of reactive power supplied by different sources and cost incurred by the system to supply active power loss. The three formulations are intended to: maximise output of inherent reactive power sources of the network, maximise the system dynamic reactive power reserve and minimise the reactive power procurement cost. Nonetheless, these techniques suffer from a lack of accuracy given that they are unsuitable to deal with the non-convexity of power systems optimisation problems [10]. Due to their better performance and efficiency, heuristic techniques have attracted increasing interest in recent years. Additionally, the emergence of FACTS devices as a means of providing voltage control, has encouraged researchers to develop reactive power management techniques taking this technology into consideration [10].

Voltage Control levels

In order to provide adequate voltage control it is crucial to provide voltage controllers with the right voltage setpoint. Furthermore, scheduling actions must be performed so as to guarantee the availability of sufficient transmission capacity and reactive power reserve. For these reasons, voltage control is divided into three hierarchical levels. These levels are separated both geographically, from local to regional or international areas, and temporarily, from a few seconds to several minutes [37].

The majority of TSOs perform voltage control by manually controlling the reactive power sources. This manual control relies on simulations based on forecasts, which introduce a certain degree of uncertainty due to variability of load and non-manageable generation. Under such scheme, it is difficult to coordinate the different controls [38].

- **Primary Voltage Control**

  Primary voltage control is intended to ensure that voltage setpoints, fixed by higher level controls or the TSO, are accomplished by reactive power sources. Primary control actions are taken in a time frame of a few seconds [37]. The primary voltage control is subdivided into [39]:

- **Unit control:** This consists basically of generator's automatic voltage regulator actuation, which is intended to regulate machine's excitation so as to maintain its terminal voltage equal to the reference value provided.
- **Plant control:** Commonly known as joint voltage control, its objective is to maintain a certain value of voltage at the plant's point of connection avoiding reactive power interchange between the plant generators.
- **Load tap changers:** Load tap changers modify the transformer's turns ratio so as to modify voltage at the secondary winding. They are important for long-term voltage stability.

- **Secondary Voltage Control**

  For security and economic reasons it is more efficient to centralize the decisions about voltage control. The secondary voltage control is in charge of adjusting and maintaining the voltage profile inside a network area [37]. It represents an outer control loop that regulates transmission-side voltage via the so-called pilot buses. In order to achieve the desired voltage profile, voltage setpoints are calculated within 30 and 100s and it is considered as a regional control [39].

- **Coordinated Secondary Voltage Control**

  The objective of coordinated secondary voltage control is to fix/approach voltage of the pilot buses to a pre-defined setpoint. Nonetheless, this control usually includes additional goals. A lower priority goal is to bind the reactive power output of each generator to a reference value so as to minimize reactive power generation and ensure reactive power reserve. According to [38], there is evidence which proves that coordinated secondary voltage control may enhance traditional secondary voltage control performance.

- **Tertiary Voltage Control**

  The purpose of tertiary voltage control is to coordinate the secondary voltage control or coordinated secondary voltage control controllers to achieve the desired voltage profile of the transmission network, attending to safety and economic criteria [37]. Tertiary voltage control provides optimal voltage setpoints for the pilot buses based on OPF calculations of different estimated system states. The time frame of tertiary voltage control ranges from 15 minutes to several hours [38]. Therefore, it can assure system integrity and security in a preventive way [39].

Primary Voltage Control

Voltage continuously fluctuates due to variations of power consumed by the loads, in addition to changes in the operating conditions of the power system. Furthermore, voltage is also affected by the losses caused by network impedances, which lead to voltage drops and yield to different values of voltage in different nodes of the system [40].

The transmission capacity of power grids is determined by the technological and economic restrictions of power systems. Thus, in order to maximise the amount of active power that can be transmitted, reactive power flows should be minimised. In order to achieve this, the required reactive power should be provided locally. This also helps to maintain voltages of the different nodes within an acceptable range.

For efficient and reliable operation of power systems, reactive power and voltage control should follow the following principles [4]:

- Voltage at the terminals of each device in the system should remain within acceptable limits. Lengthy operation outside voltage limits may adversely affect devices' performance and possibly damage them.
- Voltage and reactive power should be controlled so as to enhance system stability and maximise utilization of the transmission system.
- Reactive power flows should be minimised so as to reduce losses to a practical minimum.

Voltage control theory is based on reactive power flow theory. Reactive power flow between two nodes or substations of the system that are electrically linked may be represented as in figure 2.6.

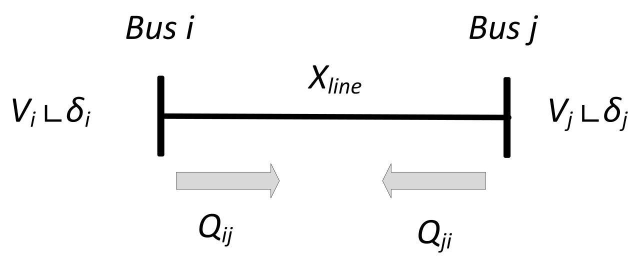

Figure 2.6: Reactive power flow representation.

Reactive power flow between two system nodes may be mathematically expressed as a function of voltage magnitude and angle difference such that:

$$Q_{ij} = \frac{V_i}{X_{ij}}(V_i - V_j cos\delta) \tag{2.1}$$

Where δ is the voltage angle difference between both nodes ($\delta = \delta_j - \delta_i$). V is the voltage magnitude at each node (i and j) and X_{ij} is the impedance of the transmission element between them. According to this, reactive power flow depends on the difference of voltage magnitude between the nodes. Additionally, it can be seen that, for small angular differences, reactive power will flow from the node with higher voltage magnitude to the one with lower voltage. The reactive power flow at both ends of the line depends on the load's current and the reactive part of the line's reactance. Reactive power flow produces a reduction in line voltage which is function of line reactance.

The reactive power consumption of a transmission element can be stated so that:

$$Q_l = Q_{ij} + Q_{ji} \tag{2.2}$$

Substituting equation 2.1 and rearranging:

$$Q_l = \frac{V_i^2}{X_{ij}} + \frac{V_j^2}{X_{ij}} - 2\frac{V_i V_j}{X_{ij}} cos\delta \tag{2.3}$$

The needs for reactive power are then determined by the square of voltages at buses i and j. Reactive power consumption of a power line increases as the difference of voltage angle between line ends increases.

Voltage control is performed by controlling a part of the production, absorption and/or flow of reactive power at all levels in the system. Generating units provide the main sort of voltage control by controlling field excitation so as to maintain the scheduled voltage at the terminals of the generator. Nonetheless, devices for additional control capacity are required to control voltage system-wide [4]. These devices may be classified as follows:

- Sources or sinks of reactive power, such as shunt capacitors or reactors, synchronous condensers and SVCs.
- Line reactance compensators, such as series capacitors.
- Regulating transformers, such as tap-changing transformers and boosters.

Therefore, voltage control methods may be based on reactive power flow adjustment, network parameters adjustment or node voltage set up [40]. However, the most effective and most utilized one is based on reactive power flow adjustment. This method lies in generating a certain amount of inductive/capacitive reactive power in order to compensate a capacitive/inductive consumption. Since voltage depends on reactive power flow, by adjusting the generated amount of reactive power, voltage may be controlled. Voltage control by reactive power flow adjustment may be continuous, which is commonly used as a primary means for voltage regulation, or discrete, which is used as a secondary means of regulation [40].

The main sources of reactive power for voltage control by reactive power flow adjustment are [40]:

- **Generators:** When the magnetic field of synchronous generators increases, the voltage at the terminals of the generator rises. Based on that principle, the automatic voltage regulator regulates magnetic field by adjusting excitation so as to achieve a certain voltage setpoint at the connection point of the generator. Electric-power generators are then an active, continuous and flexible means for voltage regulation.

- **Synchronous compensators:** Synchronous electric machines may be used only for voltage regulation, with no active power generation. These devices are referred to as synchronous compensators and their control characteristics are the same as those of generators. However, synchronous generators present an active power consumption of about a 3% of their reactive power rating.

- **Capacitors:** Capacitors may be set together in series and/or parallel in order to achieve the desired operating voltage and output current. They then become a discrete source of capacitive reactive power. Capacitor banks are usually designed so they can be partially switched by several steps, providing them with some flexibility.

- **Inductors:** In the same way as capacitors, inductors may be used for inductive power provision in order to compensate capacitive reactive power generated by the line charging effect in low load operation.

- **Static VAR compensensators:** Static VAR compensators (SVCs) are created by combining banks of capacitors and inductors. Voltage control may be performed discretely by mechanical switches or continuously by a bias winding or a thyristor control scheme.

- **FACTS devices:** Flexible AC transmission systems (FACTS) devices are power electronics based devices designed for providing flexible control of power system magnitudes. Equipped with a proper reactive power source, some FACTS devices may quickly and efficiently regulate inductive and capacitive reactive power so as to provide voltage control, congestion management, etc. Different types and characteristics of FACTS devices are described in section 2.4.

2.2 Power Systems Stability

”*Power system stability may be broadly defined as that property of a power system that enables it to remain in a state of operating equilibrium under normal operating conditions and to regain an acceptable state of equilibrium after being subjected to a disturbance*” [4].

Traditionally, the term stability has been used to describe problems related to the loss of synchronism of electrical devices. Since the main power generators are synchronous machines, it is crucial for power systems operation that they remain ”in step” at a given frequency. This is referred to as *rotor angle stability*. Nonetheless, the flow of power along the power system causes differences in voltage magnitude, as well as *phase* or *power angle* differences, which may also be kept in a certain equilibrium [4]. Furthermore, given that there is no significant storage capacity within power systems so as to accommodate load variations, it is important to coordinate generation and load [14]. This is referred to as *frequency stability*. In figure 2.7, a classification of power systems stability issues may be found.

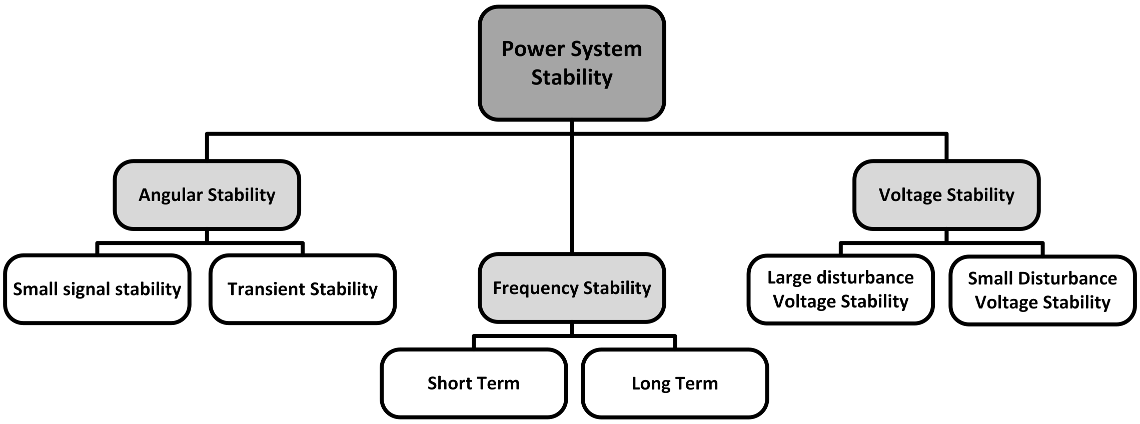

Figure 2.7: Power system stability classification [4].

For steady-state analysis, power systems are evaluated under a concrete set of operating conditions. A precise state of equilibrium is studied based on constant grid topology, generation output and load conditions. Transient stability is related to the ability of power systems to accommodate sudden changes and return quickly to a sustainable operating state. Therefore, power systems dynamic behaviour is evaluated for disturbances such as load changes, faults, loss of transmission links and failure of large generation units [14]. The aim of these studies is to evaluate whether primary control actions are sufficient to maintain the stability of the system.

Mid-term and long-term stability involve the response to contingencies that generate disturbances so great or so long-lasting that they provoke the actions of slow processes, protective systems and controls not modelled in conventional transient stability studies [4].

Small isolated power systems are particularly prone to stability issues. The relatively small size and number of generating units causes a lack of inertia. This, together with the limited control capability and the lack of flexibility of grid elements, leads to more severe instability issues [16]. Therefore, relatively small fluctuations of demand, as well as RES power, lead to profound disturbances of frequency in power systems with weak or no interconnections. When renewable penetration increases, a new stability concern arises, since conventional power needs to be taken out. In such a situation, the capability of conventional generators to reduce their output is decreased, since an operative range needs to be respected [17]. Additionally, if conventional generating units are replaced by non-manageable ones, power system inertia is further reduced.

In regard to voltage stability, isolated power systems are usually characterized by low voltage and low meshed transmission systems. On the one hand, the lack of alternative paths for electrical power harms security of supply. On the other hand, the consequent high impedance of electrical paths leads to large voltage drops and voltage stability issues. This study is oriented to steady-state voltage stability in small isolated power systems. Therefore, from here on, the research will focus on these issues.

2.2.1 Voltage Stability

As mentioned before, power systems' instability may come from the collapse of load voltage. Voltage stability is the ability of a power system to maintain voltage at all buses within an acceptable range after a disturbance. In this sense, voltage instability occurs when power systems are unable to meet the demand for reactive power [4].

The main obstacle to power flow is power losses caused by line impedances, which lead to voltage drops . Therefore, any variation in line impedances, or any reduction of available paths from generators to loads, may affect voltage profile and harm voltage stability. Furthermore, the active power that can be transmitted through an impedance from a constant voltage source is physically limited [4]. Thus, any load shift or rise may also modify both the voltage profile and voltage stability margin.

A criterion for voltage stability is that voltage control can be performed. In order to control bus voltages, controllers increase or decrease reactive power output so as to increase or decrease the voltage magnitude at the controlled bus. A system is instable in terms of voltage stability if, at any bus, an increase in reactive power output lead to a reduction of voltage magnitude or vice-versa [4]. When the maximum power transmission capability has been overtaken, a decrease in load impedance reduces power. In such a situation, depending on load characteristics, voltage may collapse or stabilize at a much lower level. The reaction of other controllers, such as under-load tap-changing transformers, may worsen the situation.

Voltage stability may be classified into steady-stated and dynamic voltage stability. When voltage stability is studied from a steady-state perspective, power flow (PF) calculations are performed so as to evaluate voltage magnitude at all buses in the power system. At the same time, voltage stability margin and steady-state voltage sensitivities are calculated or estimated.

In contrast, in regard to real-time operation, two kinds of situation may occur. A displacement from voltage equilibrium may usually be restored quickly. However, voltage oscillations may remain, specially after large disturbances. Voltage oscillations may propagate far and appear to affect large power systems more intensively [14]. Thus, dynamic voltage stability may be classified in:

- **Large-disturbance voltage stability**: Large-disturbance voltage stability is related to the ability of the power system to withstand a severe sudden disturbance, such as faults, loss of generation or line contingencies. This ability is determined by the interaction of the dynamics of controls, protections, load characteristics and dynamics. Thus large-disturbance voltage stability studies may be considered as transient stability studies.

- **Small-disturbance voltage stability**: This is related to the ability of a power system to control voltages after small perturbations such as increments of load. These studies focus on concrete power systems' configuration at a given instant of time. Static analysis may be performed so as to evaluate voltage control capabilities after different small disturbances in different system configurations.

2.2.2 Voltage Stability Indices

Traditionally, power systems' steady-state voltage stability has been studied by using different techniques. In particular, various analytical tools to predict voltage collapse, based on different concepts, have been proposed. Voltage stability indices (VSIs) derive from these techniques and allow estimating voltage instability proximity and finding the weakest bus, area or line in the system [41].

These indices are used for online evaluation of power systems' voltage stability. Following this, operators or automatic control systems can perform preventive actions so as to avoid voltage instability. VSIs can also be used offline for designing and planning studies [41].

For instance, VSIs can be used for DG placement and sizing problems in two steps. In the first one, VSI can be used for finding the weakest buses and/or lines to determine the candidate locations for DG units. Then, the optimal location can be found by maximising the voltage stability margin in terms of a particular VSI [6]. In a similar manner, VSIs can be used for FACTS devices placement [41].

The methodologies for studying voltage stability may be classified in several manners [5]. However, the authors propose a classification based on the information they need so as to be implemented. Thus, VSIs may be classified in system-variables based indices and Jacobian-matrix based indices (Figure 2.9).

On the one hand, the Jacobian-matrix based indices need the Jacobian matrix or a comprehensive set of information about the power system in order to determine the voltage collapse. These methods also allow finding the elements (buses, lines, etc.) that contribute most to voltage instability. Nonetheless, they require solving non-lineal equations, which may generate singularities [5]. Two common methodologies of this kind are V-Q sensitivity and Q-V modal analysis.

On the other hand, methodologies based on system variables employ variables (voltages and currents) and/or parameters (resistance, reactance, etc.) in order to estimate voltage instability. The values of the variables may come from power system equivalent models, power flow calculations or measurements [5]. This category includes the majority of the most important VSIs, for instance: L-index, LQP, VCPI or FVSI.

A classification of VSIs according to the type of element in which they are based on is provided in [6] . According to this classification, VSIs may be categorized as line VSIs, bus VSIs and overall VSIs.

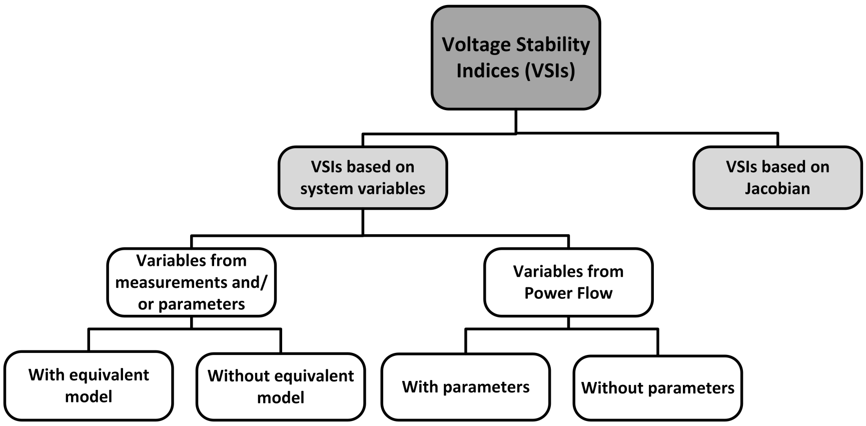

Figure 2.8: Voltage stability indices classification according to the information they are based on [5].

Voltage stability may be evaluated by the voltage stability of a line. Line VSIs are formulated in terms of the two-bus representation of a power system. Thus, the model of a power system used in all line VSIs is the same, and the differences are related to the assumptions made. Alternatively, bus VSIs provide information about voltage stability of system buses, but they cannot be used for the determination of weak facilities. Overall VSIs are not related to power system's elements, so they can only predict the system collapse point in terms of load, and not the weakest elements in the system [6].

One of the main advantages of methodologies based on measurements is that they allow for analysing voltage stability in different operating conditions in a straightforward manner. Thus, they allow power systems online monitoring. Nonetheless, one of the challenges that this approach involves is the huge amount of information needed to evaluate voltage stability in big power systems. This has been partially solved by strategically selecting pilot buses so as to ensure a whole system observability. Another interesting feature of variable-based VSIs from measurements is that some of them involve the load's dynamic characteristics. Although this is not a wide-spread feature, it permits performing analysis closer to a power system's real conditions [5].

On the other hand, methodologies based on variables coming from PF calculations are less time consuming. Since they are based in simple equations, they are suitable for big power systems. One of their main disadvantages is that they sometimes depend on the power system's parameters. Thus, if real data is not available, the reliability of the results may be endangered. Furthermore, these approaches are often based on the principle of maximum power transfer from a power grid to a constant load. This can lead to inexact results due to the effect of dynamic loads in real power systems [5].

In recent years, artificial intelligence (AI) has increasingly become a useful technique for voltage stability analysis. In these approaches, indices based on variables coming from PF have been widely employed as supervised training schemes have been used. At the same time, the quality and availability of data for the calculation of indices based on measured variables has

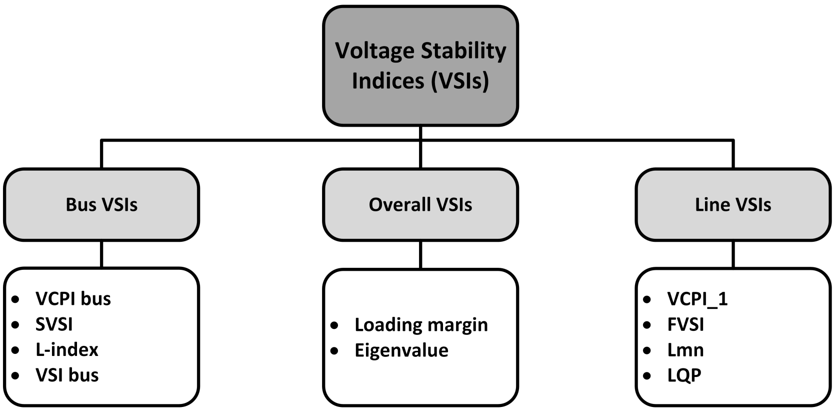

Figure 2.9: Voltage stability indices classification according to the grid element they are referred to [6].

increased thanks to the inclusion of phasor measurement units in power systems [5].

In [41], the performance of several variable-based indices calculated from PF are compared. The authors found that various bus and line indices identified the critical line and buses correctly. A comparison of static VSIs in dynamic simulations is done in a similar manner in [42]. The authors found all indices' behaviour coherent with their theoretical formulation. Furthermore, they found that, for a 39-bus benchmark system, the top ten weakest lines of the system coincided for $VCPI(p)$ and L_{mn} with a maximum difference of two places.

Subsequently, the main VSIs are described following the categorisation proposed in [5].

VSIs based on the Jacobian Matrix

- **V-Q sensitivity**

  The V-Q sensitivity represents the slope of the Q-V curve at a given operating point. Thus, it is a measure of the voltage variations caused by the amount of reactive power at the load buses[4].

  The constraints of a power transmission network may be expressed in the following linearized form:

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_{P\theta} & J_{PV} \\ J_{Q\theta} & J_{QV} \end{bmatrix} \begin{bmatrix} \Delta\theta \\ \Delta V \end{bmatrix} \tag{2.4}$$

  where ΔP is the incremental change of bus active power, ΔQ is the incremental change of bus reactive power, $\Delta\theta$ is the incremental change of bus voltage angle and ΔV is the incremental change of bus voltage magnitude. So as to evaluate V-Q sensitivity, ΔP is assumed to be 0. Therefore, equation 2.4 can be simplified so that:

$$\Delta Q = J_R \Delta V \tag{2.5}$$

where:

$$J_R = [J_{QV} - J_{Q\theta} \quad J_{P\theta}^{-1} J_{PV}] \tag{2.6}$$

and J_R is the reduced Jacobian matrix of the power grid.

The matrix J_R^{-1} is the inverse reduced V-Q Jacobian, and every element of its diagonal is the V-Q sensitivity of every bus in the power grid. Positive values indicate stable operation, and V-Q sensitivity rises when stability decreases, becoming infinite at the voltage collapse point. When the system becomes unstable, V-Q sensitivity take negative values. Therefore, this method may be used for voltage stability margin estimation. Nonetheless, despite providing information about the combined effects all V-Q variation modes, it cannot identify an individual voltage collapse mode [4]. Since V-Q sensitivity is dependent on both the loading conditions and the admitance matrix, this analysis needs to be performed for different loading levels and/or other operating conditions.

- **Q-V Modal Analysis**

  In Q-V modal analysis, eigenvalues and eigenvectors of the reduced Jacobian matrix J_R are used to estimate the voltage stability characteristics of a given power system (equation 2.7). Firstly, eigenvalues provide a relative measure of the proximity to voltage collapse, but not an absolute one. Secondly, eigenvectors provide information about elements that contribute to voltage instability, such as critical nodes or areas [4]. According to this, the V-Q sensitivity may be stated as follows:

$$\Delta V = \sum \frac{\xi_k \eta_k}{\lambda_k} \Delta Q \tag{2.7}$$

  Where ξ_k is the k^{th} column of the right eigenvector, η_k is the k^{th} row of the left eigenvector and λ_k is k^{th} eigenvalue. Positive values of all eigenvalues would mean that the power system is stable in terms of voltage stability. The lower the eigenvalues are, the nearer to instability the power system is. If one or more eigenvalues become negative, that would mean that the system is no longer stable. Consequently, if one or more eigenvalues become zero, the power system would be at a critical point in terms of voltage stability.

VSIs Based on System Variables

- **Overall VSIs**

  Overall VSIs convey the robustness of the system as a whole against voltage collapse. In this section, loading margin, reactive power margin and the L-index are described.

  - **Loading Margin**

The simplest case of power system can be represented as a constant voltage source that feeds a load through an impedance (figure 2.10). In such a situation, there is a maximum value of active power that can be transmitted for a fixed power factor [4].

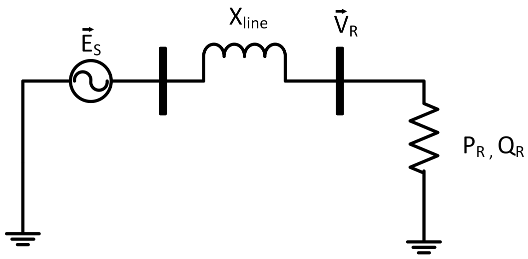

Figure 2.10: Transmission line's model.

For any value of active power at the receiving end (P_R) such as $P_R < P_{Rmax}$, we can find two operating points. On the one hand, at the upper point (A), any decrease in P_R results in an increase of V_R (figure 2.11). On the other hand, at the lower point (B), any decrease in P_R results in an decrease of V_R. Since voltage controllers are designed to operate in region A, when operating in region B the system becomes instable. Hence, the conditions in which $P_R = P_{Rmax}$ represent the limit of satisfactory operation. The values of voltage and current corresponding to that point (C) are referred to as *critical values* [4]. When dealing with complex power systems, the situation in which the voltage in one or more nodes inevitably falls is referred to as *voltage collapse*.

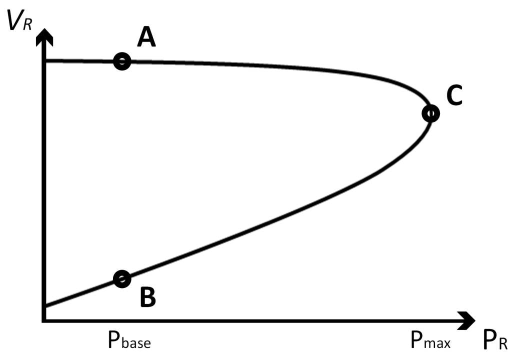

Figure 2.11: P-V characteristic of a transmission line.

Using PF analysis, we can calculate the *critical values* at which *voltage collapse* occurs for a given power system. Starting from a given *loading level* (P_{init}), load is iteratively increased (and PF is calculated) until the *voltage collapse* occurs (P_{max}). Thus, loading margin (λ) can be defined as:

$$\lambda = (P_{max} - P_{init})/P_{init} \tag{2.8}$$

– **Reactive Power Margin**

The Q-V curves are produced by successively performing PF calculations with increasing values of reactive power at the selected buses. Hence, the Q-V curves represent the relationship between reactive power and voltage at a certain bus (see figure 2.12). The bottom of the curve (point A), where the derivative dQ/dV equals zero, determines the voltage stability limit and the amount of reactive power needed to avoid it. As for the P-V curve, the design of the control devices determines that the system is stable in the right side of the curve, where an increase in reactive power leads an increase in voltage. Q-V curves allow determining the amount of reactive power needed to hold a certain voltage level at a given bus. For buses without reactive power generation or absorption, the operative point is located on the x axis (point B).

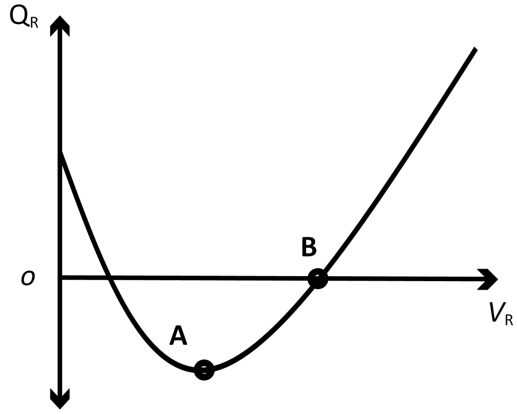

Figure 2.12: Q-V characteristic of a transmission line.

– **L-index**

The L-index is a quantitative measure of the estimated distance between the actual state of the power system and the stability limit. This index is calculated as the maximum among a set of local indicators L_k. Thus, it permits the determination of the nodes which may originate a voltage collapse [43]. The L-index is formulated as follows:

$$L_k = \left| 1 - \frac{\sum\limits_{i \in \alpha_G} F_{ki} V_i}{V_k} \right| \tag{2.9}$$

$$L = \max_{k \in \alpha_L} \quad L_k \tag{2.10}$$

Where α_G is the set of generation buses, α_L is the set of load buses, V is the voltage of a certain bus and F is a submatrix of the partial inversion of the Y-matrix (H-matrix).

The L-index is a simple and robust measure for estimating stability margin of a power system in case of uniformly distributed load rise. Nonetheless, local load increments and line outages may be treated specifically [43].

- **Line VSIs**

In line VSIs the power flow along the lines is evaluated in both directions, from the receiving end and from the sending end of the line [44]. According to the two-buses power system model in figure 2.10, active power entering the receiving end may be described as follows:

$$P_j = P_i - \frac{R_{ij}(P_i^2 + Q_i^2)}{V_i^2} \tag{2.11}$$

Where i and j are the sending and receiving buses of the line being evaluated. R_{ij} is the resistance of the line, P is active power, Q is reactive power and V is voltage.

Reshaping equation 2.11, we found that:

$$\frac{R_{ij}}{V_i^2} P_i^2 - P_i + P_j + \frac{R_{ij}}{V_i^2} Q_i^2 = 0 \tag{2.12}$$

Equation 2.12 provides two solutions for P_i, which may be real, being true that:

$$1 - 4\frac{R_{ij}}{V_i^2}(P_j + \frac{R_{ij}}{V_i^2} Q_i^2) \geqslant 0 \tag{2.13}$$

This equation represents a line VSI based on active power flow at the sending end of the line. In the same way, indices for reactive power referred to the receiving end of the line may derive from equation 2.13. Additionally, making different assumptions, distinct indices have been proposed (see table 2.1).

Index	Name	Equation
LFISP	Line flow index based on P_S	$4\frac{R_{ij}}{V_i^2}(P_j + \frac{R_{ij}}{V_i^2} Q_i^2)$
LFIRP	Line flow index based on P_R	$4\frac{R_{ij}}{V_i^2}(-P_i + \frac{R_{ij}}{V_i^2} Q_j^2)$
LFISQ	Line flow index based on Q_S	$4\frac{X_{ij}}{V_i^2}(Q_j + \frac{X_{ij}}{V_i^2} P_i^2)$
LFIRQ	Line flow index based on Q_R	$4\frac{X_{ij}}{V_i^2}(-Q_i + \frac{X_{ij}}{V_i^2} P_j^2)$
L_{mn}[45]	Line Stability Index	$L_{mn} \frac{4Q_j X_{ij}}{(V_i sen(\theta - \delta))^2}$
LQP [46]	Line Stability Factor	$LQP = 4\left(\frac{X_{ij}}{V_i^2}\right)\left(\frac{X_{ij}}{V_i^2} P_i^2 + Q_j\right)$

Table 2.1: Line voltage stability indices based on power system variables.

- **Bus VSIs**

Similarly, bus voltage stability indices have been proposed by different authors taking advantage of power system equations. A selection of bus VSIs is presented in table 2.2.

Index	Name	Equation
$FVSI$ [47]	Fast Voltage Stability Index	$FVSI = \frac{4Z^2Q_j}{V_i^2X_{ij}}$
$VCPI_1$ [48]	Voltage Collapse Proximity Indicator 1	$VCPI_1 = \frac{P_j}{P_{jMAX}}$
$VCPI_2$ [48]	Voltage Collapse Proximity Indicator 2	$VCPI_2 = \frac{Q_j}{Q_{jMAX}}$

Table 2.2: Bus voltage stability indices based on power system variables.

In summary, VSIs may be classified into system-variables based indices and Jacobian-matrix based indices [5]. However, the fist show some advantages that make them preferable for FACTS placement studies. One of their main advantages is that they allow for analysing voltage stability in a straightforward manner [5]. Therefore, these indices provide insights in a way that is more easily interpreted by researchers and/or engineers. Furthermore, since PF may be used to calculate system variables, more precise results may be obtained in comparison to indices based on the Jacobian matrix. For these reasons, variable-based VSIs have been chosen as the basis of the proposal for FACTS devices impact assessment. In particular, PF will be used for simulating several demand scenarios from which VSIs will be calculated.

It is worth mentioning that indices based on variables coming from PF have been widely employed in combination with artificial intelligence algorithms. Thus, by using this kind of indices, our methodology may be able to integrate such a solution for future studies.

On the other hand, a choice on the kind of VSIs according to the grid element they are referred to needed to me maid. Given that a shunt FACTS device (STATCOM) will be used in this work, line VSIs may be discarded. Thus, only overall and/or bus VSIs will be considered.

2.3 Performance Index Selection Method

As mentioned before, several indices based on power system variables, either coming from measurements or PF calculations, are frequently used for voltage stability assessment, and particularly for FACTS devices placement [5]. Nevertheless, indices are not usually selected in a systematic manner, but by heuristic procedures based on experience and expertise of system planners or researchers [49]. When facing the selection of appropriate indices for FACTS devices placement, diverse determinants arise. Some of them are the measurement or calculation method accuracy or the index representativeness, accuracy and comparability.

Despite the fact that accessing to all the necessary information is frequently troublesome, a production system may be characterized by analysing a set of quantities, or indices, that may be easily measured. These are commonly indirect measurements of the desired variables based on other variables, but they are used as a proxy for them, and may be treated as analytical variables or aggregated to create higher-level indices [50]. In the context of business intelligence, machine learning and big data, these indices are called key performance indices (KPIs) [51].

Common indices are usually selected due to historical use rather than because of a quantifiable utility, obscuring their actual benefit. The lack of clear criteria lead to a dependence on implicit knowledge of decision-makers. On the other hand, systematic approaches allow for a more general application of index selection processes [49].

For accurate decision-making, it is not only important to understand the relationship between system quantities and every index, but also to identify and characterise the inter-dependencies among the different indices. The addition of information about inter-dependencies will provide better and more realistic performance estimations of a production system and the selected indices [50].

A compromise between a sufficiently large information content and cognitive capacity of decision-makers needs to be reached. The selected index system should be as simple as possible, with a number of indices high enough to include sufficient information, and as low as possible so as to be manageable for the decision makers [49].

Frameworks for index selection attempt to structure the discussion process in a systematic manner. Alternatively, analytical approaches use methods like correlation analysis ([52] and [53]) and the analytical hierarchy process or analytical network process ([54] and [55]).

With the same aim, in machine learning and data mining, feature selection is used to find the smallest feature subset which provides the most comprehensive information about a system or process, or to find the subset with n features that provides the most comprehensive information [56]. In this context, a feature (also named attribute or variable) is a property that has been measured or derived from the original input variables. Irrelevant or redundant features may hide the existence of relevant ones, leading to inaccurate and inefficient simulation [57].

2.3.1 Mutual Information

Mutual information (MI) may be used to perform feature selection. In the context of information theory, mutual information measures the amount of information that a certain variable, index or feature shares with another [56]. Thus, it is a measure of the mutual dependence between two variables. The MI is usually used, instead of the correlation coefficient, when it is necessary to measure high order dependencies [58]. The MI is intimately related to the entropy of a random variable, which conveys the expected amount of information contained in it.

The entropy is a measure of the level of uncertainty associated to the expected results of a random variable. The uncertainty is linked to the probability of the occurrence of an event; a high entropy means that every possible event has the same probability of occurrence, while a low entropy means that different events have different probability [56]. If every event has the same probability, it is impossible to predict the occurrence of a concrete one. In conclusion, the entropy conveys the lack of knowledge about the expected behaviour of a random variable, given that it measures the uncertainty incurred when trying to predict it. Given a discrete random variable X, whose different values $x_i,...,x_n$ may occur with probability $P(x_i),...,P(x_n)$, the entropy of X is given by the equation 2.14.

$$H(X) = -\sum_{i=1}^{n} P(x_i)\log P(x_i) \tag{2.14}$$

If X is a continuous random variable, which is the case of multiple power systems variables, its related probabilities become a probability density function (PDF) and summations are changed by integrals. Therefore, given a continuous random variable X, its entropy is given by the equation 2.15.

$$H(X) = -\int p(x)\log p(x)dx \tag{2.15}$$

Where $p(x)$ is the probability density function of X.

Similarly, the ”joint entropy” of two random variables may also be calculated. The joint entropy measures the uncertainty related to the joint occurrence of values from two different random variables. Therefore, it determines how confident one can be when trying to predict values from two variables at the same time. In other words, it determines to what extent the joint (and simultaneous) behaviour of two variables is unknown. If we take two continuous random variables as X and Y, their joint entropy is given by equation 2.16.

$$H(X,Y) = -\int\int p(x)p(y)\log p(x,y)dxdy \tag{2.16}$$

Where $p(x)$ and $p(y)$ are the PDFs of X and Y, respectively, and $p(x,y)$ is the joint PDF of both variables.

In a context such that variables, or attributes, are treated as stochastic, the MI between two variables is a measure of the mutual interdependence between them. The MI equals zero when two variables are statistically independent and augments as long as the relationship between them gets stronger. For this reason, the MI is used to analyse statistical dependency between random variables [57]. For continuous variables, the MI is defined as follows:

$$I(X;Y) = \int\int p(x,y)log\frac{p(x,y)}{p(x)p(y)}dxdy \tag{2.17}$$

Where X and Y are continuous random variables whose PDFs are $p(x)$ and $p(y)$, and $p(x,y)$ is the joint PDF of X and Y. Therefore, $p(x,y)$ determines the probability with which certain values of X and Y may appear at the same time.

As mentioned, the MI is tightly related to the entropy. The relationship between them, for discrete random variables, is ruled by the following equations (2.20).

$$I(X;Y) = \begin{cases} H(X) - H(X|Y) \\ H(Y) - H(Y|X) \\ H(X) + H(Y) - H(X,Y) \end{cases} \tag{2.18}$$

Where $H(X|Y)$ is the conditional entropy between two variables. This measures the uncertainty of predicting values from one variable knowing the values of another, and is defined as follows:

$$H(X|Y) = -\int\int p(x,y)\log p(x|y)dxdy \tag{2.19}$$

The MI may be interpreted as the distance between variables, given that large values imply large dissimilarities or "distances". Nonetheless, it is useful to derive a metric, in the strict sense, from the MI [59]. Based on the MI, different variations, and particularly different metrics, have been proposed. For instance, the variation of information is a distance metric related to the mutual information. The variation of information ($d(X,Y)$) may be interpreted as a measure of the discrepancy between two random variables (X,Y) in terms of information theory. This may be computed as follows:

$$d(X,Y) = \begin{matrix} H(X,Y) - I(X;Y) \\ H(X|Y) + H(Y|X) \\ H(X) + H(Y) - 2I(X;Y) \end{matrix} \tag{2.20}$$

However, $d(X,Y)$ is a non-normalised metric, and its results may be biased by the size of the "sample" used to characterize each index. A normalized metric may be more appropriate for the case of index selection, since it enables us to measure the "distance" between two indices, in terms of shared information, irrespective of the size of the sample. Additionally, since we have to compare "similarities" between pairs of indices, a normalized metric ensures a fair comparison in all cases. A very common normalized metric is D [60], which may be computed as follows:

$$D(X,Y) = \frac{d(X,Y)}{H(X,Y)} = 1 - \frac{I(X;Y)}{H(X,Y)} \tag{2.21}$$

The $D-distance$ is suitable for this purpose given that $D(X,X) = 0$ and $D(X,Y) \leq 1 \quad \forall(X,Y)$.

According to equation 2.21, D provides small values when the joint entropy is small, and consequently the MI is high, meaning that X and Y are similar. If the $D-distance$ is greater than 0, X and Y are statistically dependent. If the $D-distance$ equals 1, it means that X and Y reflect the same reality and thus they are the same variable. Therefore, D has been used as measure of the complementarity of the information provided by the different indices for index selection.

In our case, the mutual information is computed based on Shannon entropies, taking advantage of the following expression:

$$I(X;Y) = H(X) + H(Y) - H(X,Y) \tag{2.22}$$

Where $H(X)$ y $H(Y)$ are the marginal entropies of the variables X and Y, and $H(X,Y)$ is the joint entropy of both variables.

2.3.2 Entropy and Mutual Information Estimation

The calculation of the entropy, and particularly the joint entropy, is crucial to ensure a good performance of the MI-based index selection method. In order to compute the entropies, it is necessary to know the probability density distribution of every variable. Additionally, in the case of the joint entropy, it is also necessary to know the joint probability density distribution of every pair of variables. Given that the data used to represent the behaviour of every index derive from a sample of the actual disaggregated power system demand, its density distribution is unknown. Therefore, a probability density estimation method needs to be implemented. However, there are some issues that may affect the accuracy of the results.

It is worth pointing out that the procedure of estimating the density functions for the MI estimation is biased [61]. The error caused by this bias may accumulate during the procedure of feature selection [62], so it needs to be taken into consideration. This effect may become more relevant in case of large sets of features with small number of samples. To reduce the MI estimation error, it is important to enhance the accuracy of the computation of PDFs. In this context, histograms may be used as a simple and efficient method for PDFs. estimation.

In order to build a histogram, the range of values within a sample of a given population is divided into a number of bins. The bins are consecutive non-overlapping, and often equal-width, intervals of the variable. The histogram is constructed by counting the number of samples of the variable that fall into each bin. Therefore, histograms provide a piece-wise frequency distribution. If the histogram is normalised by the number of samples, it will represent relative frequencies, with the sum of the height of the rectangles totalling 1.

Some issues related to the number of bins and their inner distribution condition the accuracy of this method. On the one hand, it is crucial to attend to the influence of the number of bins on the final result. As demonstrated in [63], if we augment the number of bins to reduce the error in our estimation of the density, we can find an increase of the variance in our estimates. Therefore, a trade-off between estimation error and variance needs to be found when choosing the number of bins. On the other hand, the traditional formulation of histograms implies that the probability density is uniform inside each bin. Based on this piece-wise estimate of a continuous density, the accuracy of the histograms is also limited [63].

Different solutions have been proposed to mitigate these problems. For instance, different methods have been put forth to estimate the optimal number of bins, or bin width, based on the assumption of a particular probability distribution of the samples ([64] and [65]). In [61], a method is proposed for estimating the number of bins for low bias histogram-based MI estimation. However, this method is only suitable for Gaussian distributions. Nonetheless, if the underlying distribution is unknown, it is not reasonable to perform an optimisation based on the error between the obtained density and the "true" density [66]. In [66], a method for estimating the optimal number of bins, given a sample of unknown density distribution, is proposed. This method takes advantage of Bayesian probability theory to estimate the optimal number of bins for any density distribution with good results for small samples. Nevertheless, due to the implemented search strategy, its computation may be too slow when dealing with multidimensional data or large data sets that require a big number of bins. Alternatively, so as to reduce the bias, the size of the bins may be adaptive, which provides promising results but at a high computational cost [61]. Additionally, some authors have proposed more sophisticated ways to assign a distribution to the density of each bin using a Bayesian approach [58].

Therefore, the main issues concerning density estimation are related to the number of bins. However, from our knowledge, there is no appropriate method to select an optimal number of bins. On the one hand, traditional methods rely on the assumption of a particular density distribution. On the other hand, enhanced methods are not properly tested for large samples and bi-dimensional data. Consequently, an iterative process have been carried out to search for the number of bins that ensures a robust result. A description of this procedure, as well as the results of its implementation, can be found in the appendix.

2.3.3 Index Selection Methods Based on Mutual Information

Several feature selection methods derive from the MI; such as common mutual information, joint mutual information [67], conditional infomax feature extraction [68] or the conditional mutual information-based feature selection [69]. MI-based feature selection algorithms aim at minimising the joint MI between the selected features and a target variable. However, estimating high-dimensional MI from high-dimensional data entails large computational complexity [57]. Consequently, different algorithms, such as minimal redundance maximal relevance (mRMR) [70], mutual information feature selection [71] or normalized mutual information Feature Selection [72] have been proposed to avoid the calculation of high-dimensional joint mutual information.

In order to find an optimal subset from the original feature set, a search strategy needs to be implemented. Optimal search strategies imply exhaustive search and accelerated methods [56]. For feature subsets of p features out of m, p^m possible subsets may exist; thus, an exhaustive search is impractical for large sets of features [56]. Consequently, sub-optimal search strategies, such as sequential forward selection and sequential backward elimination, are frequently used. These methods suffer from nested effect and are prone to delivering suboptimal results, since they do not take into account the interdependence of different features [57].

In the context of power system analysis, MI-based methods have been used for feature selection in a handful of studies. In [73] MI is used to exclude insignificant features before voltage stability assessment is performed. In [74] feature extraction is performed using MI as an objective function within an online transient stability assessment procedure. In [75] and [76] mRMR is used to find a reduced feature set for transient stability assessement. Additionally, a symmetrical uncertainty mRMR method is proposed in [77] for feature selection in the context of wind farms fault source identification.

mRMR is a common solution for feature selection in power systems assessments since it is a fast and greedy heuristic [78]. However, given the exponential dimensionality of feature selection, and since mRMR does not take into consideration the interactions between different subsets, it does not guarantee an optimal solution. In fact, distinct sets of equivalent or better quality may exist. For this reason, a parallelised version of the mRMR algorithm is proposed in [78]. In the proposed solution, the computation burden still needs to be reduced by computing MI score between features in a lazy-evaluation manner. Similarly, AI techniques are commonly used for a more efficient sub-set sampling. This approach is used in [79] for oscillatory stability assessment.

In conclusion, performance indices are usually selected on the basis of non systematic procedures, which are dependent on the expertise of researchers or engineers. Thus, a systematic index selection method is needed. An interesting family of approaches for index selection is the one used in machine learning and data mining, called *feature selection*, which is used to find the smallest feature subset which provides the most comprehensive information about a system or process [56].In this regard, mutual information becomes an interesting tool for index selection. MI measures the amount of information that a certain variable, index or feature shares with another [56]. Therefore, it may be used to find those indices that provide the most complementary information about the problem, leading to a more comprehensive solution.

In this work, MI has been used for index selection. However, MI is a non-normalised measure of the dissimilarity between two variables. Instead, a normalised metric (D) has been used for this purpose.

2.4 Flexible AC Transmission Systems (FACTS)

Power systems are very often highly interconnected, involving connections within the utilities' influence area, connections between utilities from different areas and inter-regional and international connections. These interconnections are needed because, beyond simply delivering power, transmission networks are intended to minimise the total generation capacity and operation cost by pooling power plants and loads. Moreover, in deregulated power systems, a sufficient transmission capacity is needed to ensure a competitive environment as well as reliable electric service [80].

Rapid changes in demand, generation technologies and operation paradigms have occurred recently. With the increase of power transfers, power systems become more vulnerable to major outages and more difficult to operate [80]. In addition, transmission expansion planning is being frustrated by environmental, land-use and regulatory issues that complicate, or even prevent, the construction of new transmission and generation infrastructures [19].

The increase of transmission requirements, the absence of long-term planning and the need to provide open access to generating companies and customers in deregulated environments, has led to power systems being operated in a more stressed and less secure manner, reducing the quality of supply [80].

The increase of renewable power and the restrictions to transmission grids' expansion has led to a crossroads in regards to the aim of power systems planners to ensure the availability of a reliable electrical supply. These problems could be solved by setting up new power plants and transmission lines or repowering the existing ones. These approaches, however, involve lengthy construction times, large investments and various environmental, legal and social difficulties [19]. This is especially true for small territories, such as islands, in which land is scarce and the decision about which new infrastructures need to be set up, and where to do it, is frequently conflicting.

The demands of lower transmission losses, faster response to operative changes, and higher system stability have led to the development of flexible AC transmission systems (FACTS). FACTS are compensation systems based on power electronics and connected to transmission lines in series or shunt [40]. FACTS technologies enable modification of the electrical characteristics of transmission elements much more rapidly than traditional tools, even in real time. Therefore, they allow increasing operating efficiency and reducing operative constraints without the need for including new major infrastructures [14].

Consequently, FACTS provide added flexibility that enable power lines to transmit power near to their thermal capacity. Nonetheless, FACTS technology is not a one-on-one substitute for mechanical switched compensators, but rather a complement so as to provide an enhanced VAR compensation. Since different technologies may be combined and modularity may be used in FACTS design, this technology also permits a step-by-step planning with incremental investment based on operation requirements [80].

2.4.1 Description of FACTS devices

FACTS are alternating current transmission systems based on power electronics and other static controllers intended to control power networks in a flexible manner [20]. The usefulness of this technology is based on its ability to control shunt and series impedance, as well as voltage and phase angle, and to damp oscillations at various frequencies below the rated frequency [80]. FACTS technology comprises a wide range of solutions that lead to the development of different controllers. FACTS controllers are static equipment, mainly power electronic-based devices, that provide control of one or more AC transmission systems parameters [20]. According to [80], FACTS devices may be basically classified in four categories:

- **Series controllers:** The series controllers inject voltage in series with the line, they could be a variable impedance, such as capacitor or reactor, or a variable source based on power electronics. The injected voltage is usually in phase quadrature with the line current, so series controllers only supply or consume reactive power.

- **Shunt controllers:** The shunt controllers inject current into the system at the point of connection. Like the series controllers, they may be a variable impedance, a power electronic based variable source or a combination of both. Again, as long as the injected current remain in phase quadrature with the line voltage, shunt controllers only supply reactive power.

- **Combined series-series controllers:** They could be a combination of independent series controllers controlled in a coordinated manner in a multi-line transmission system. Alternatively, they could be a unified controller composed of various series controllers which are linked together so they can provide independent series reactive compensation for each line, and also transfer active power among the lines through the power link.

- **Combined series-shunt controllers:** They may be a combination of separate series and shunt controllers controlled in a coordinated manner or a *unified power flow controller* with series and shunt elements. The term ”unified” means that the DC terminals of all converters are connected together for real power transfer.

Therefore, series controllers are able to modify the current and power flow directly. Thus, they are much more effective for controlling current and power flows and damping oscillations than shunt controllers. A solution based on series controllers may require several separated controllers for different lines. However, this may not be decisive since the required MVA size of the controllers for series applications is small compared to shunt applications [80]. On the other hand, shunt controllers perform better as a bus voltage controller despite the number of lines connected to the bus. For these reasons, a combination of series and shunt controllers may provide a wider solution, enabling current and power flow control, as well as line voltage

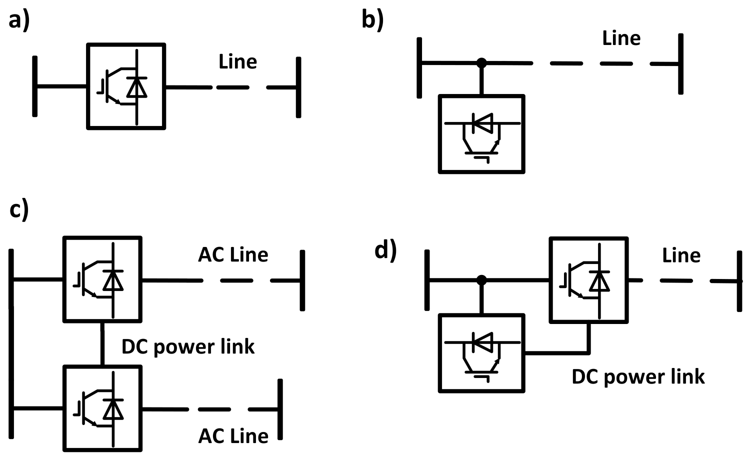

Figure 2.13: Schematic representation of different types of FACTS: a) Series FACTS, b) Shunt FACTS, c) Series-series FACTS and d) Series-shunt FACTS.

control [80]. A schematic representation of the basic types of controllers can be found in figure 2.13.

Both series and shunt controllers are able to host energy storage, as shown in figure 2.14. A significant improvement in system dynamics control is achieved by adding storage to a controller. Furthermore, different storage devices, with different characteristics, such as batteries, superconducting magnets or supercapacitors, may be used for this purpose.

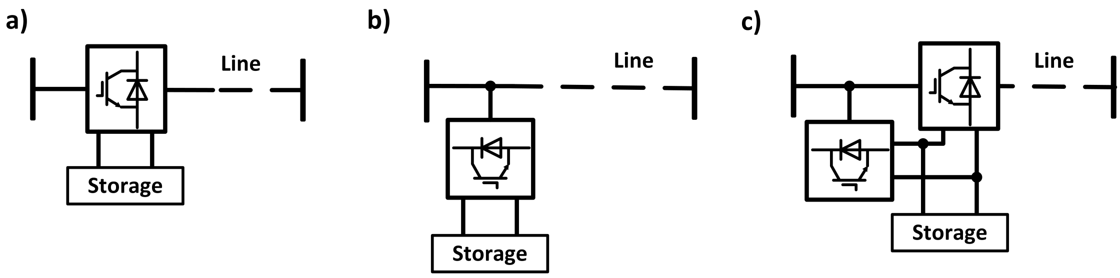

Figure 2.14: Schematic representation of different types of FACTS including energy storage: a) Series FACTS, b) Shunt FACTS and c) Series-shunt FACTS.

FACTS devices may be also classified into two main categories or ”families”; namely, thyristor-based controllers and voltage source controllers (VSCs).In figure 2.15, one can find a classification of power flow control devices according to their nature and connection mode [40].

The first generation of FACTS devices were basically power electronic versions of existing compensating technologies that took advantage of conventional unidirectional thyristors [19]. More recently, FACTS devices have been designed to take advantage of DC to AC converters, which are based on thyristors with gate turn-off capabilities [80]. These devices may provide reactive power control, but also active power control using either the energy stored in the converter itself or an additional storage [80]. A converter may be designed to provide a precise

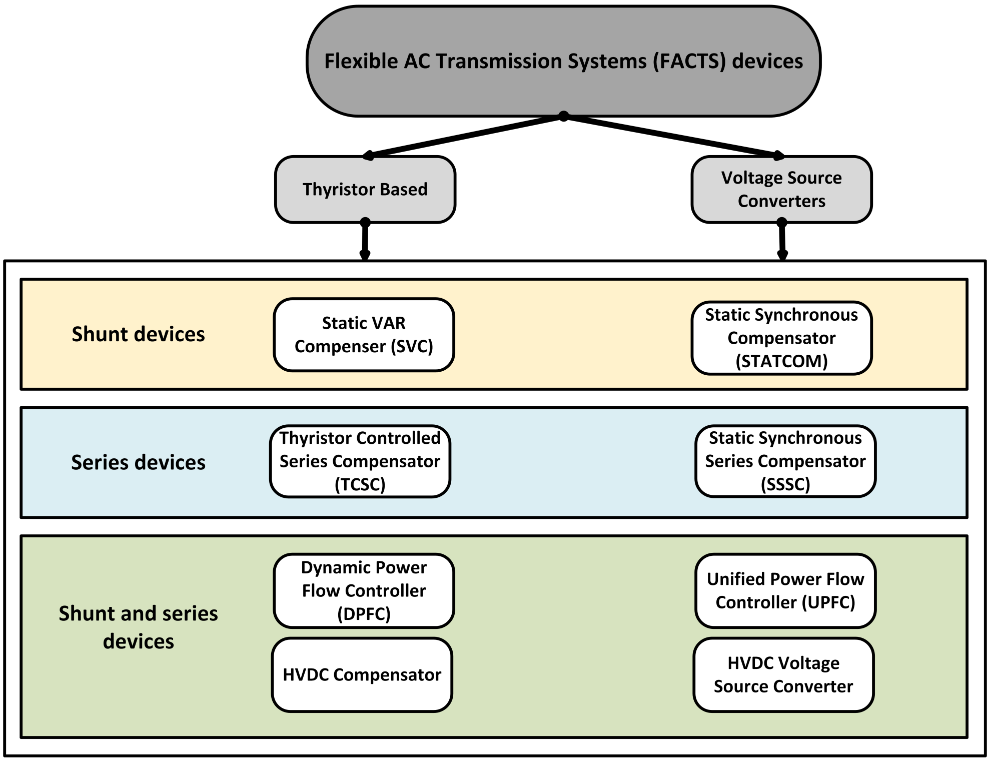

Figure 2.15: Classification of different power flow control devices.

waveform for harmonics suppression or to derive power between phases so as to balance unbalanced systems.

Controllers based on conventional thyristors

The first designs of FACTS controllers were based on conventional thyristors that switched a reactive power source on and off. More recently, fast-acting series compensators were designed using thyristors so as to vary the impedance of key transmission lines with almost no delay [19]. The main thyristor based controllers are described below.

- *Thyristor-Switched Reactor/Capacitor*

  Thyristor-switched reactor/capacitor (TSRs/TSCs) are formed by several shunt connected inductors/capacitors that are switched in and out step-wise by thyristor switches without any firing angle control. Therefore, they are unable to perform continuous control [80].

- *Thyristor-Controlled Reactor*

  The thyristor-controlled reactor (TCR) is composed of a linear reactor and a controller, which is basically an anti-parallel thyristor pair that conducts on alternate half-cycles of the grid frequency. Thus, the reactor behaves as a shunt-connected controllable inductance based on the firing angle of the controller [19].

- *The Static VAR Compensator*

Basically, a static VAR compensator (SVC) is formed by a TCR in parallel with a bank of capacitors, which enables it to generate or absorb reactive power continuously. Therefore, a SVC is able to perform voltage regulation at its point of connection in a continuous manner. The firing angle control of the SVC permits almost instantaneous response [19].

- *Thyristor-Controlled Series Compensator*

  The thyristor-controlled series compensator (TCSC) is a series device comprising one or more modules composed by a TCR in parallel with a fix capacitor. The TCSC varies the impedance of the line to which it is connected, providing a fast active power flow regulation [19].

Controllers Based on Fully Controlled Semiconductor Devices

Modern controllers for power system applications are based on more sophisticated power electronic converters. These controllers act as an interface between the DC side of the converter and the AC grid. The DC source may be a voltage source (typically a capacitor) or a current source (typically a voltage source in series with an inductor). For both economic and performance reasons, voltage source converters (VSCs) are often the preferred choice for reactive power compensation [19]. The main VSCs are described subsequently.

- *The Static Synchronous Compensator*

  The static synchronous compensator (STATCOM) is defined as a static synchronous generator which is operated as a shunt-connected SVC whose capacitive or inductive output current can be controlled independent of the AC system voltage [80]. Several different devices derive from the combination of STATCOMs with other devices, especially distinct active power sources.

- *Battery Energy Storage System*

  Battery energy storage systems (BESS) are chemical-based storage systems that use shunt-connected VSCs, frequently STATCOMs, to regulate the amount of energy that is supplied to or absorbed from an AC system. Therefore, they are able to provide a significant amount of active power for transient stability applications while also providing reactive power for voltage regulation [80].

- *Static Synchronous Series Compensator*

  A static synchronous series compensator (SSSC) is a self-commuted switching power converter with no external source of power operated as a series compensator. The SSSC increases or decreases the overall reactive voltage drop across the line to which it is connected so as to control the power flow by regulating the output voltage. The SSSC may include an energy storage so as to provide transient active power compensation [80].

- *Interline Power Flow Controller*

  The interline power flow controller (IPFC) is the combination of two or more SSSC installed in different power lines and coupled via a common DC link. Thus, they are able to manage real active power flow of the different lines [80].

- *Unified Power Flow Controller*

  The unified power flow controller (UPFC) is a combination of a STATCOM and a SSSC joined by a common DC link. It is able to provide concurrent real and reactive line power flow control, as well as bus voltage regulation, without the need of an external electric energy source [80].

Static Synchronous Compensators

As mentioned earlier, VSCs are the most well-established FACTS devices due to their good performance. Among them, the static synchronous compensators (STATCOMs) stands out. Thanks to their flexibility and fast response, they have become a very useful solution for many different issues related to power systems stability and power quality. In any case, STATCOMs may be used on their own, as well as in combination with other devices, for a wide variety of applications. A particularly useful combination is to add an energy storage to a STATCOM so as to enable it to provide active power control.

In this study, STATCOM technology has been chosen to represent FACTS devices capabilities for voltage control. Therefore, a brief overview on STATCOM's applications is provided below.

The STATCOM is composed of a capacitor, which acts as a voltage source, and a series of fast electronic switching devices; mainly IGBTs or GTOs (Figure 2.16). STATCOMs are intended to dynamically generate or absorb reactive power in a fast and robust way, since no moving parts are involved and low voltages do not affect their operation [19].

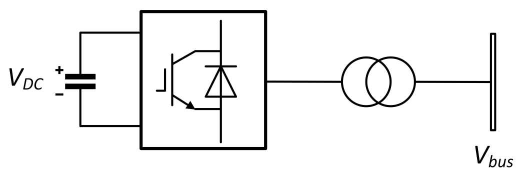

Figure 2.16: Schematic representation of a STATCOM device.

STATCOMs have been used in many different applications due to their flexibility and simplicity. They provide flexible and quick reactive power control since current coming from the DC bus is rectified by the bi-directional electronic switches. Additionally, if an energy storage is connected to the DC bus, STATCOMs are enabled to exchange both active and reactive power [81]. Different implementations have been studied to tackle different power system operation issues. In [82] models for steady-state and transient representation of a STATCOM for voltage and voltage angle stability are presented. Under common power system analysis assumptions, the models demonstrated to capture both the steady-state behaviour and the dynamics of the device. In this research, the effectiveness of STATCOMs in providing voltage control is addressed, since they ptoved to be capable of maintaining the desired voltage at the connection point by providing the required reactive power. In [81], a dynamic model of a combined STATCOM-Flywheel solution is presented and a multi-level control technique is developed in order to mitigate instabilities caused by wind power plants. By adding an active power source to the STATCOM architecture, and with an appropriate control strategy, power fluctuations coming from wind power plants are effectively absorbed. In addition, voltage or power factor control are also enabled by this configuration. A similar approach is proposed in [83] for damping regulation, and a comparative study between STATCOM and BESS functionalities is presented as well. By connecting and disconnecting the BESS from the DC bus, active power capabilities are added to a STATCOM. Furthermore, a comparison between local and remote control signals is performed. Results show the effectiveness of both STATCOM and BESS functionalities in reducing power oscillations. However, BESS proved to be more effective for this purpose. Additionally, remote control signals showed better results than local signals for damping oscillations in STATCOM mode.

STATCOMs have also been used for providing reactive power for voltage regulation, eliminating harmonics and balancing supply currents for unbalanced systems in distribution networks, as stated in [84]. In this paper, a comprehensive study of several topologies and various control techniques for Distribution STATCOMs (DSTATCOMs) is performed. Some design considerations are also described and differences are stated between three-phase three-wire and three-phase four-wire DSTATCOMs and between isolated and non isolated ones. A particular implementation of a DSTATCOM for voltage regulation and load balancing is presented in [85]. DSTATCOMs have proven their efficacy in reducing distribution losses [86] and augmenting the amount of photovoltaic power that radial distribution systems can handle [87]. Furthermore, in [88] a demonstration of satisfactory performance of DSTATCOMs in current compensation, harmonic elimination and load balancing is provided. Similarly, a study on voltage control and reverse power flows mitigation is presented in [89]. A DSTATCOM is used to recirculate power between different phases in lines where reverse flows are observed. A comparison between low-voltage and medium-voltage applications, considering specific filter arrangements, is performed. Voltage control is found to be more effective in low-voltage feeders, while unbalanced current compensation showed better performance in medium-voltage feeders.

2.4.2 FACTS Devices Applications

As mentioned above, FACTS provide the possibility of modifying electrical characteristics of transmission elements in a fast and flexible manner. Based on this principle, FACTS devices are able to perform several control actions so as to increase operating efficiency and relieve transmission constraints, avoiding the construction of major new infrastructures. According to the survey presented in [7], the applications of FACTS devices may be classified into two categories attending to the power system issues they may relieve (see figure 2.17).

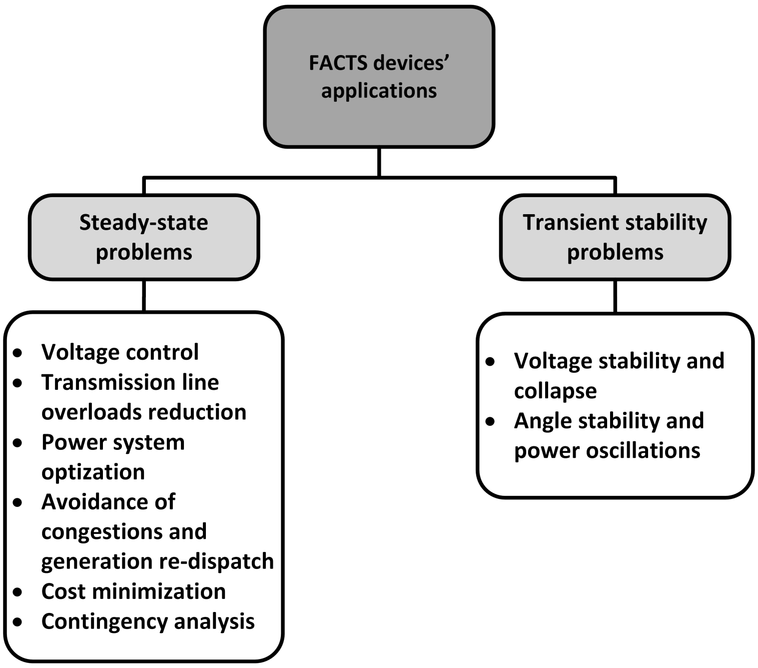

Figure 2.17: Classification of FACTS application according to power systems' issues [7].

In [10], a summary of different FACTS devices and their applications is provided. The number of applications of each type of device is merely representative, and actual applications of different technologies may overlap. Nonetheless, the summary, which can be found in table 2.3, may serve as an overview of the capabilities of FACTS devices and their differences.

Distributed FACTS (DFACTS) have been proposed as a solution for the integration of distributed generators (DGs) based on RES in electrical distribution networks. DFACTS provide the traditional power quality enhancement solutions of FACTS, but with reduced size and cost [11]. They are also easier to implement compared to conventional FACTS. As can be seen in table 2.4, the performance of DFACTS devices for power quality enhancement depends on the type of technology considered.

The expansion of RES in power systems has led to a change in the policy of electrical utilities in relation to control, reliability, management, power quality, and protections, as a distributed generation scheme has increasingly prevailed. The shift to distributed systems may entail the simultaneous installation of DGs and FACTS devices. The interactions between these devices may either enhance or deteriorate power system's stability depending on their tuning and placement [25]. Furthermore, it is important to highlight that adverse interactions may occur when more than one FACTS devices are implemented in the presence of DGs. Adverse current and voltage interaction problems between DGs and FACTS can be minimised by equalising DGs' and FACTS's terminal voltages in order to reduce the circulating currents among them [25]. Consequently, optimal coordinated placement and control of the devices is needed.

Device	Applications
TCSC	System stability enhancement
	Sub-synchronous resonance mitigation
	Load-flow control
	Power oscillations damping
TCSR/TSSR	Stepped series inductance achievement
	Voltage regulation
	Variable inductive reactance smoothing
SSSC	Line impedance control
	Series compensation control
	Independent voltage and current control
	Power oscillations damping
TSR	VAR absorption
	Inductive and capacitive current exchange
	Short-circuit current limitation
STATCOM	Transient stability enhancement
	3-phase unbalance correction
	Voltage flicker retrainment
	Voltage regulation
	Line loss reduction
SVC	Power oscillations damping
	System stability enhancement
	Reactive power dynamic control
	Voltage quality improvement
UPFC	Two-way power flow control
	Reactive/active power compensation
	Line impedance control
	Transmission angle control

Table 2.3: Applications of different types of FACTS devices [10].

Interactions between generators and FACTS devices may be classified as steady-state interactions and generator or machine-related interactions, according to [90]. Steady-state interactions are related to steady-state voltage stability, reactive power reserves and power transfer capability of the system. Generator or machine-related interactions comprise two types of dynamic interactions: electro-mechanical interactions, related to interactions occurring in small and large disturbances, and subsynchronous resonance interactions, related to the exchanges of energy between the electric system and the generator torsional system. Interactions may also occur between different FACTS devices in form of interactions between control actions or high frequency interactions [90].

2.4.3 FACTS Devices Impact Assessment Techniques

In order to assess the impact of FACTS devices in power systems performance, a myriad of different techniques have been developed. The main objectives considered by researchers when

Attributes	**IPQC**	**DSSSC**	**DSTATCOM**	**UPQC**
Reactive compensation	Good	Poor	Best	Best
Harmonic suppression	Adjustable	Adjustable	Adjustable	Adjustable
Resonance	No	May exist	No	No
Load balancing	Good	Good	Best	Best
Transient stability	Good	Good	Better	Best
Steady-state stability	Good	Good	Better	Best
Voltage control	Good	Good	Best	Best
Power rating of converter	Small	High	High	Small
Number of switches	9-12	6	6	12
Overall Cost	Medium	Low	Low	Medium
Performance in hardware design	Good	Good	Better	Best

Table 2.4: Performance comparison of DFACTS devices [11].

using these techniques are the size, location and best type of FACTS devices to be used, as well as the different combinations of these objectives. Furthermore, coordination between different FACTS devices has been also studied [8].

Despite the technical benefits that FACTS present for power system operation enhancement, cost effective analysis should be also performed before a decision in this respect is made. Usually, financial and business viewpoints are considered first, considering cost and advantages, since different short or mid-term financially viable alternatives may exist [12].

From a technical perspective, FACTS devices impact assessment problems are complex multi-objective optimisation problems involving several variables with highly non-linear relationships. Multi-objective problems have more than one objective, and often these objectives are conflicting. Thus, there is no single optimal solution able to simultaneously optimize all objective functions. Instead, decision makers look for the ”most preferred” solution. In this context, the concept of optimality is substituted by that of Pareto optimality, in which an optimal solution is the one that cannot be improved in one objective function without deteriorating the other(s) [91].

Optimal FACTS (and DGs) placement multi-objective problems have been traditionally formulated as: a) a single objective function computed as the weighted sum of the individual objectives, b) a single objective function using the goal programming method and c) a compromise solution selection among a set of feasible solutions considering more than one objective [25]. Therefore, a single-objective tool is used by reformulating the problem to consider the multiple objectives. To this end, preferences are set among the different objective functions. Given their simple structure, these traditional optimization methods became very useful and popular in the past. However, they are associated with some shortcomings [10]. Lately, heuristic multi-objective algorithms have been developed with enhanced results. In particular, population-based schemes have demonstrated better performance in these kinds of problems with the need to perform fewer trials to find a solution and avoid the sensitivity to the Pareto front shape [10].

In [8], a taxonomical survey on optimization techniques used to assess power system enhancement due to FACTS devices is presented. According to the authors, these techniques may be classified in five different categories: conventional, optimization, artificial intelligence-based, hybrid and current techniques. This classification substantially coincide with the ones elaborated in [25] and [92]. The proposed categories and their most significant techniques are described subsequently.

- **Conventional methods**: These are based on technical criteria derived from a particular power system analysis method, such as sensitivity analysis. They are usually based on performance and stability indices for steady-state analysis and modal analysis for dynamic or transient assessment [7]. Some of the most common conventional methods are briefly described below. A more detailed description may be found in [8].

  – **Modal analysis**: This is based on the analysis of the dynamic characteristics of the system in the frequency domain.

  – **Index method**: This is based on one or more measures that convey the goodness of the solution. When more than one index is used, they are aggregated, commonly using a weighted sum.

  – **Controlling method**: This seeks to develop a control model that yield an optimum control of the system, avoiding overshoot and ensuring control stability.

  – **Sensitivity based-method**: This analyses the relationship between input and output variables.

  – **Eigen-value method**: This uses the eigen-values (Ev) of the impedance matrix of the system as a measure of power system's stability.

- **Optimization techniques**: These are based on mathematical equations from which an optimal solution of the problem emerges. This optimization is performed through an iterative process that can be solved by different methods, such as liner programming, mixed-integer non-linear programming, and others [7]. Some of the most frequently used are the following [8].

  – **Linear programming**: This is an optimization technique intended to deal with real valued linear objective functions subjected to linear equality and inequality constraints.

  – **Mixed-integer non-linear programming**: Mixed-integer non-linear programming (MINLP) is used to solve problems involving continuous and discrete variables.

  – **Analytical approach**: This is a strategy to solve difficult problems by sub-diving them into the necessary sub-parts.

  - **Optimal power flow**: OPF uses optimisation techniques to optimize active and reactive power flow, as well as voltage magnitude and angle, collected from a conventional power flow calculation.

- **Artificial intelligence-based techniques**: Also termed as heuristic and meta-heuristic methods, artificial intelligence (AI)-based techniques are computational methods based on stochastic sets of candidate solutions. By iteratively selecting or generating new candidate solutions, AI techniques try to optimise the objective function(s). These techniques can be divided in: swarm-based algorithms, evolution-based algorithms and hybrid algorithms [92]. Some of the most relevant are the following [8].

  - **Genetic algorithm**: Genetic algorithm (GA) is a particular type of evolutionary algorithm that optimises an objective function by iteratively generating new sets of candidate solutions using bio-inspired operators such as crossover and selection.
  - **Artificial neural network**: This is formed by a collection of learning algorithms that interact towards a common objective resembling neurons in a biological brain. Artificial neural networks are trained using pre-solved examples from which they ”learn” with no need of pre-programmed rules.
  - **Fuzzy linear programming**: This uses fuzzy logic in order to address uncertainty and imprecision of engineering problems. Fuzzy logic uses membership functions to convey the degree of association of an element to a given set, ranging from 0 to 1. Fuzzy logic implements human experiences and preferences via membership functions and rules [25].
  - **Particle swarm optimisation**: Particle swarm optimisation (PSO) optimises a problem by improving a candidate solution with regard to a given measure of quality. Each candidate solution (particle) ”moves” towards a better solution based on the quality of its own existing solution, but also influenced by the best positions among the particles belonging to its swarm (population).

- **Hybrid techniques**: These are methods that take advantage of two or more techniques so as to improve the analysis’ results. The most frequent hybrid solution is composed of an optimization technique ruled by an AI-based technique [8].

- **Current techniques**: These are different kinds of methods that have recently been developed. Some of the most relevant are the following [8].

  - **Energy approach method**: This is based on linear behaviour and energy conservation to provide optimal solutions to energy-related problems such as planning and operation of energy production and consumption units.

- **Active control technique**: In this technique, an adjustable speed machine is used as a synchronous condenser connected to a flywheel so as to provide active and reactive power supply to the system in transient studies.
- **Passivity method**: This is based on the concept of ”passive element”, which is very common in the fields of analogue electronics and control systems. A passive component may be either a component that consumes but do not generates power or a component that is incapable of power gain.
- **Pole placement**: This is a method for controller design in which controller parameters are optimized by determining the places of the control loop system poles on the complex plane.

According to the survey carried out in [8], there is a well-balanced distribution of the different FACTS devices assessment techniques classes. However, looking at the results in detail, two classes stand out. If we look at the hybrid techniques, we find that all of the techniques comprised are in fact either optimization or AI-based techniques. Thus, special attention needs to be paid to these techniques and their interactions.

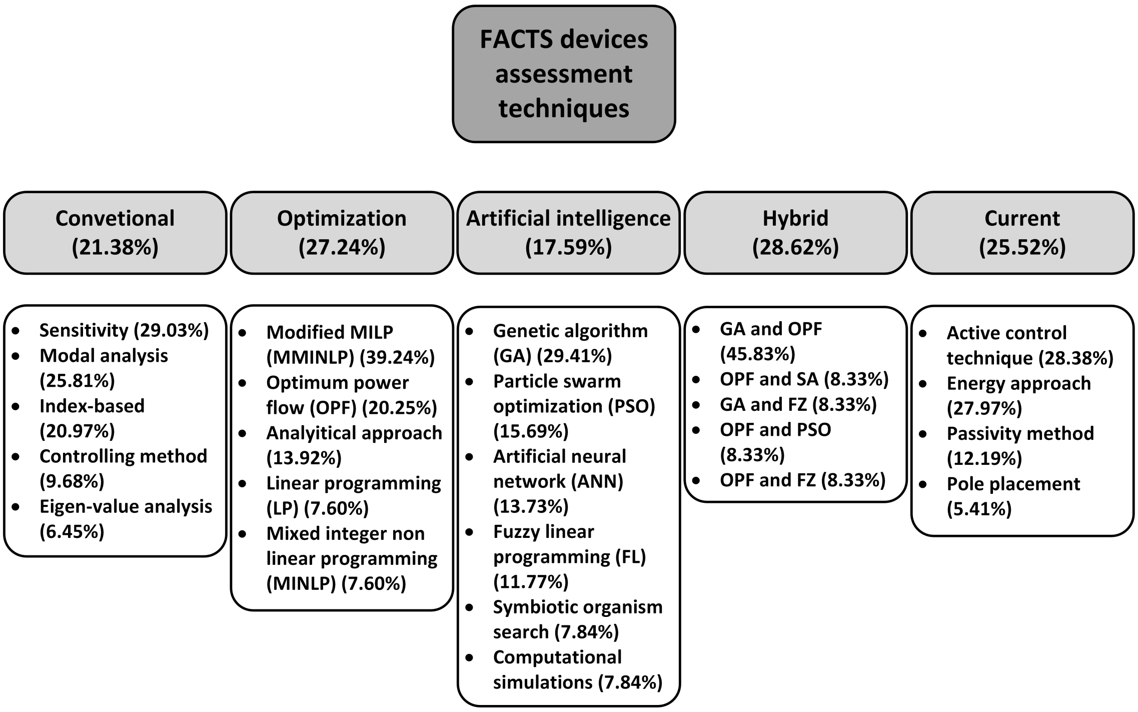

Figure 2.18: Classification of FACTS devices assessment techniques. Elaborated based on the survey carried out in [8].

Traditional optimisation techniques provide considerable results and thus became very popular at one time. However, they were not designed to handle multiple objectives, so they become more complex when dealing with such problems. Furthermore, the representativeness of their results was reduced by the assumptions made to address multiple objectives. In particular, when a ”weighted” approach was used, the obtained solution was conditioned by the relative values of the specified weights [10].

A particular multi-objective approach is the Pareto approach. This approach uses the concept of ”Pareto optimality” to select a set of non-dominated solutions within a great number of solutions. The decision maker has no influence on the development of the procedure, and he or she can only intervene once the Pareto set is found [10]. Once the computation process is finished, a solution may be selected from the Pareto set on the basis of fuzzy set theory. Nonetheless, these algorithms are costly in computational terms because they need a great number of trials to generate Pareto-optimal solutions. Moreover, due to their lineal approximation, they fail to account for all non-dominated solutions and only those positioned on the convex part of the Pareto front can be evaluated [10].

In the recent decades, meta-heuristic approaches have gained huge attention due to their fast and high-quality performance. Two techniques stand out at this point due to their wide spread use both on their own and in combination with other techniques. On the one hand, PSO has become very popular thank to its simple implementation and its efficiency to solve complex problems. However, PSO algorithms suffer from premature convergence when facing complex problems [25]. On the other hand, GA has been used profusely due to its efficiency despite some drawbacks such as divergence and local minima problem [25]. Nonetheless, results may be improved by combining two or more AI techniques or combining AI techniques with traditional optimization techniques.

2.4.4 FACTS Devices Placement

Size and location are key to an optimal use of FACTS devices. Nonetheless, several studies have demonstrated that finding the best solution to this problem is not an easy task. Some authors have proved that, in certain cases, the weakest bus is not the best location for compensation in terms of voltage stability enhancement [21]. Furthermore, others have found that the need for reactive power is determined by the required capacity under contingency state [93].

A particularisation on FACTS devices assessment techniques for FACTS devices placement is done in this section, paying special attention to the way in which load variations are considered in the existing literature. The FACTS devices placement is part of the core studies aimed to assess FACTS devices impact on power systems. Therefore, analysis and optimization techniques described previously are fully applicable to this problem. Researchers have employed and combined different techniques in order to study the effects of the inclusion of this technology in power systems, particularly in relation to its optimal placement. Most of them are based on one of the different power flow (PF) methods, namely: PF, continuation power flow (CPF), optimal power flow (OPF) and voltage security constrained OPF (VSCOPF).

Conventional analytical techniques were first used for FACTS devices placement taking advantage of the PF method. In this approach, PF calculations provided the core information about power system operation from which different indices could be derived so as to predict voltage collapse [41]. In addition, indices of the efficiency of power system operation may also be calculated. Two main strategies have traditionally been used for FACTS devices placement. The first attempts focused on finding the weakest bus as the optimal location, while more recent approaches have taken advantage of the greater computation capacity to test the effectiveness of the device at different locations. In [44], a method for critical line segment identification is derived from PF calculation. The line segment with maximum corrected voltage drop is considered as the best location for placing a FACTS device. In [94], voltage is used to find the weakest bus and voltage collapse proximity index (VCPI) and line stability index (LQP) are used to find the critical line in order to optimally place FACTS devices. In [95] steady-state voltage stability indices such as VCPI and LQP are used to find the optimal placement of a UPFC based on a dynamic analysis of voltage stability. The results of the proposed solution are compared to PSO and DE results. Similarly, CPF is used to predict power system's performance in stressful conditions by iteratively augmenting system load based on a driving vector. In [96] CPF is used to find the weakest bus so as to optimally place and size a STATCOM in terms of loading margin and voltage magnitude enhancement. In [97], CPF is used to estimate the loading margin for SVC placement and multi verse optimization is used to optimally tune the device. In contrast to these methods, rather than augmenting system load in a proportional manner, congestion in certain areas may be studied based on PF calculation and sensitivity factors [98].

Traditional optimization techniques based on PF methods have also been used for FACTS devices placement. Particularly, the OPF algorithm has been modified so as to assess FACTS devices operation. OPF methods usually include security constraints in order to ensure feasible solutions; these algorithms are referred to as VSCOPF algorithms. For instance, in [99] a modified version of the OPF algorithm is designed to explicitly represent FACTS devices, including series impedances and shunt current injections. An equality constraint to enforce the power balance among the converters is included, as well as voltage security constraints. Different combinations of FACTS devices are tested. From OPF and VSCOPF algorithms, different measures of power system operation may be derived and single-objective optimizations may be easily implemented. However, if a multi-objective optimization is needed, additional tools must be used. From here on, we will refer to both OPF and VSCOPF algorithms as OPF algorithms, assuming that voltage stability constraints are usually included in the formulation of the algorithms.

Recently, meta-heuristic optimization techniques have become the preferred technique for tackling these problems since they are highly efficient dealing with multi-modal, highly constrained, multi-objective and discrete problems [9]. The ε-constraint method (ε-CM) has been used for multi-objective optimization in combination with fuzzy decision-making to optimally place FACTS devices attending to generation costs, real power loss, system loadability and device cost [91]. The ε-CM is based on optimising every single objective at a time, using the remaining objectives as constraints. A similar approach, including fuzzy decision-making (FDM), has been used to place FACTS devices so as to maximize system loadability and reliability [100]. In [101], a FDM-based solution is proposed for STATCOMs optimal placement in terms of loading margin, voltage deviation and reactive power loss.

Nonetheless, the most remarkable techniques are AI-based techniques, which have been used profusely in recent times. In these approaches, the FACTS devices placement problem is divided in two sub-problems. The lower-level sub-problem is related to finding the cheapest operation configuration, and it is usually solved by OPF algorithms. The higher-level sub-problem is to determine the optimal locations of FACTS devices, and it is frequently addressed by AI techniques.

Population-based AI techniques have been used in plenty of different situations and combined with other techniques. In particular, PSO algorithms have been widely used for FACTS devices placement. In [102], a Pareto-based FACTS devices placement method is proposed to maximise system loadability and minimise device costs under contingency conditions. PSO is used to perform a guided search for Pareto-optimal solutions. In [103], a hybrid PSO-sequential quadratic programming method is used to find the optimal placement and size of FACTS devices attending to their profitability and considering contingencies and wind power in a market-oriented environment. In [104], two population-based AI techniques are combined for FACTS devices placement and sizing. PSO is used to enhance the performance of gravitational search algorithm (GSA) by optimising the gravitational constant. In [105], a self-adaptive firefly algorithm (S-AFA) is used in combination with PSO to optimally place a TCSC according to various objective functions.

Evolutionary AI techniques have also shown a remarkable popularity in research studies. For instance, differential evolution (DE) algorithms have been used to reduce operation costs by optimally placing FACTS devices accounting for demand and wind power variations [26]. More importantly, GA algorithms have been used for this purpose from different perspectives. In [106], GA is used for the search of non-dominated solutions of FACTS devices placement attending to voltage stability, real power deviation of generators and device costs. A compromise solution is then chosen according to a fuzzy membership function representing the degree of satisfaction of the aforementioned objectives. A long-term techno-economical approach is presented in [107]. In this work, GA is used to find the optimal location of FACTS devices by minimising operative costs, including device costs. A long-term economical analysis is derived from the obtained results.

A great number of different objective functions have been used to assess the impact of FACTS devices in power systems. However, since FACTS devices are particularly effective for voltage regulation and power transmission management, objective functions related to these issues predominate. According to [9], almost 30% of reviewed research articles included objective functions to maximise voltage security, followed by device cost and power loss minimisation objective functions, appearing with the same percentage, 20%. These results may be seen in figure 2.4.4.

The cost of FACTS devices may be divided into establishment cost and operation and maintenance (O&M) costs. A general guideline for O&M costs evaluation is to set their annual value between $5-10\%$ of establishment costs [12]. Approximate establishment costs for different sizes of FACTS devices are given in table 2.4.4.

Type	100 MVAR	200 MVAR	300 MVAR	400 MVAR
SVC	60	50	45	40
SVC*	100	80	70	70
STATCOM	90	75	68	60
STATCOM*	130	115	110	100

*includes installation costs

Table 2.5: FACTS devices' cost in $\$/kVAR$ [12].

In recent decades it has become more and more common to take into account the 'externalities' due to power systems' activities. For this reason, social welfare and environmental objectives functions have increasingly been introduced into power system expansion studies [3]. Greenhous gases (GHG) emissions have been added to these procedures in order to assess the environmental impact of power systems operation [108].

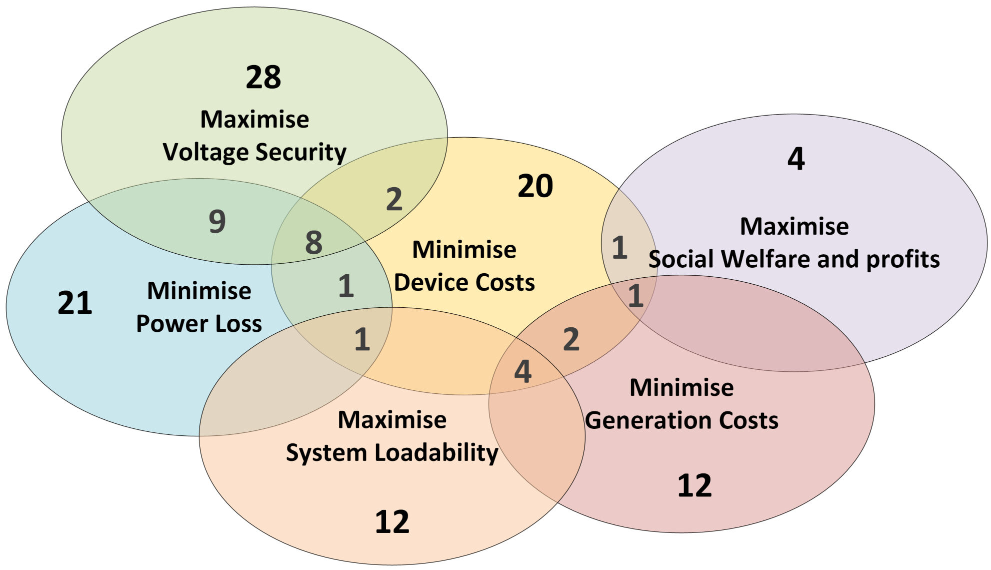

Figure 2.19: FACTS devices placement techniques attending to their objective functions. Elaborated based on the survey carried out in [9].

One of the main limitations of FACTS devices placement procedures is that they are usually based on one or a few snapshots of the power system, since they only take into account a reduced number of network configurations, load and generation dispatch scenarios, etc. Another classical approach to power systems expansion planning problems, very common in the electric power delivery industry, is focused on peak and valley demand situations, which in the end, entails the same limitations.

As mentioned in [26], the presence of some types of renewable generators in power systems entails the risks of their intermittency. This can have an important effect on the results of the placement procedure, since the impact of FACTS devices may not be adequately assessed if the number and configuration of operation scenarios are not properly selected. In fact, the authors have noted an inconsistency with classical methodologies, since they have demonstrated that peak demand is not always the best system configuration for running a FACTS allocation solver, since it may not ensure the optimal solution. Nevertheless, neither load scenarios, nor renewable power scenarios are frequently considered so as to ensure the robustness of the results.

In [9], a survey on FACTS devices placement procedures attending to the number of load scenarios is presented. The results show that 60% of the surveyed papers considered a single load scenario, 98% considered less than 7 scenarios and only one of them took into account 7 or more different load scenarios, precisely 21 (see figure 2.4.4). Identical results were obtained in relation to load variations considered as a contingency case. In this regard, 60% of reviewed articles did not consider load variations as a contingency, while 40% of them did. Load variations are, in fact, the most common contingency, followed by line outages (20%). In spite of this, several studies did not consider any kind of contingency, and only 2% took into account different types of contingencies with load variations. Additionally, most of studies did not account for the stochastic nature of power system and did not consider probabilistic approaches to FACTS devices placement.

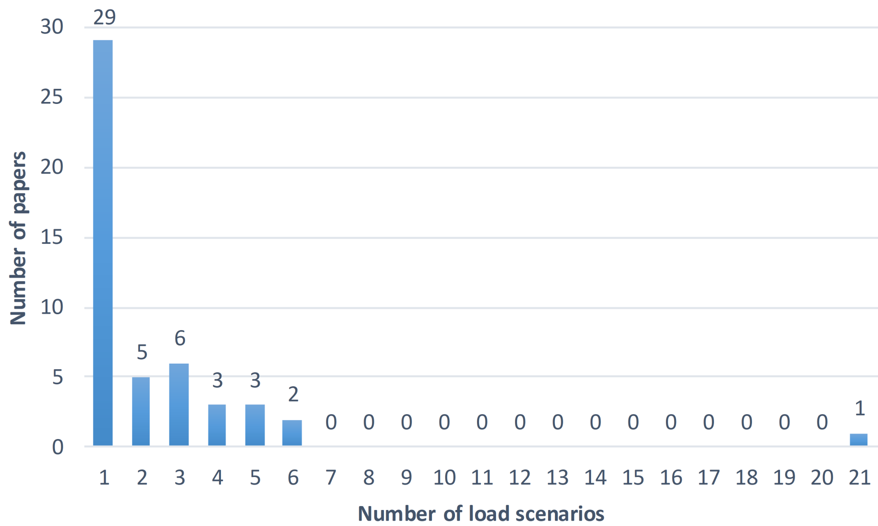

Figure 2.20: Number of papers on the topic versus number of load scenarios used. Elaborated based on the survey carried out in [9].

Nonetheless, some research articles have been found to provide systematic approaches to demand (and wind power) representation in FACTS devices placement studies. In [26], Monte Carlo simulation (MCS) is used to generate demand and wind power hourly scenarios to represent a year of power system operation based on different probability density functions. Furthermore, different strategies to reduce the number of simulations, while ensuring the results' robustness, were proposed. In [109], demand and wind power are modelled using mean hourly profiles to represent a year of data. Up to 10 years of power system operation are modelled so as to evaluate long-term economic impact of FACTS devices.

In Table 2.4.4 a brief survey on FACTS devices allocation procedures focusing on system configuration is shown. As can be seen, only one of them takes into account demand variations (as well as generation), while two of them take into account contingency states.

Paper	**FACTS Type**	**Indices**	**Method**	**Conting.**	**Demand**
[21]	STATCOM	Ev, VD, Size	FDM + GA	No	No
[26]	TCSC	Cost, Energy	MCS + DE	No	Yes
[91]	HFC, PST, UPFC	Cost, P-Loss, λ, Inv	ε-CM + FDM	No	No
[100]	DSSC	λ, EDC	Pareto + FDM	Yes	No
[101]	STATCOM	λ, VD, Qloss	FDM	No	No
[102]	SVC	λ, Cost	PSO	Yes	No
[103]	SVC, TCSC, UPFC	λ	GA	No	No
[104]	UPFC, IPFC	L-index and P-Loss	PSO + GSA	No	No
[105]	TCSC	P-Loss, VD, L-index	S-AFA + PSO	No	No

Table 2.6: Brief literature review on FACTS devices placement procedures.

To summarise, FACTS devices placement in electrical power systems is a complex non-linear multi-objective problem that has been faced using many different techniques. Despite their limitations, conventional optimizations techniques, such as OPF and heuristic and meta-heuristic techniques, such as fuzzy logic, PSO or GA, have been widely used with remarkable outcomes. In particular, different combinations of these techniques have shown enhanced results. Alternatively, Pareto optimality has frequently been used as an alternative to the aforementioned methods. In this work, a FACTS devices placement solution is proposed based on Pareto optimality. This decision is based on two main reasons. First of all, Pareto optimality is inherently a tractable multi-objective decision method. In contrast, traditional techniques are not designed for multi-objective implementations, and meta-heuristic approaches become ”black boxes” whose decisions are not tractable by human reasoning. Secondly, despite the fact that the Pareto approach requires a greater amount of simulations, time and computation requirements are not a limitation for transmission expansion planning studies. In terms of practicality, the Pareto approach allows for a visual representation that is easy to understand. Furthermore, from the perspective of transmission systems expansion planners, the multiple trade-off solutions provided by this approach may be useful.

As mentioned previously, many different objective functions have been used for evaluating FACTS devices placement solutions along with these techniques. Voltage stability objective functions are the most common, followed by device's cost and system losses. Recently, social welfare and environmental objectives functions, particularly greenhouse gases emissions, have been used. In this research, loading margin and reactive power loss have been used to assess voltage stability. Additionally, operative costs and active power losses have been used to measure the impact of the FACTS device on the system's efficiency. Greenhouse gases emissions have also been considered in order to evaluate the influence of FACTS devices on the environmental impact of power systems.

Nonetheless, this review has found that most FACTS devices impact assessment techniques do not take into account load variations. Changes in the amount and distribution of power system load may affect the results of these studies, specially in the presence of renewable generators providing non-manageable power. Therefore, there is a need for procedures that consider these interactions so as to provide robust results. This is important both for restructured market-oriented power systems and for small isolated power systems. The main goal of this research is to develop a new FACTS devices impact assessment technique intended to evaluate several disaggregated demand scenarios.

2.4.5 Voltage Control Using FACTS Devices

FACTS devices provide the capability of varying some internal variables so as to control one or more different power system variables. Therefore, the way in which this control is performed is a determining factor when trying to enhance power systems operation. This section is intended to provide a brief overview of how FACTS devices control is performed. Nonetheless, since this research is aimed at evaluating steady-state voltage stability, we will focus on voltage control.

As previously mentioned, several types of FACTS devices have been developed, and each of them may be used to tackle different power system issues. However, a particular type of devices has become very popular due to its performance and flexibility, particularly regarding voltage control. STATCOMs have been used as a solution for many operation issues, both by themselves and in combination with other devices. Their design enables them to regulate voltage almost instantaneously. Additionally, their control capabilities are not limited by operating conditions, apart from security constraints. Therefore, they are a suitable alternative for synchronous compensators. A brief review on strategies for voltage control using FACTS devices, and particularly STATCOMs, is provided subsequently.

Given the flexibility that STATCOMs provide, different control strategies and algorithms have been developed. On the one hand, traditional control strategies and tuning methods have been applied to STATCOM control. For instance, in [110] a two-level STATCOM control is described and tested. This control is composed of an internal control, intended to manage the output voltage waveform so as to comply with the demanded magnitude and phase, and an external control, which determines the reference values for the internal control. This is a common feature in STATCOM implementations. In this work, the H_∞ control approach is used in the internal control so as to provide a robust nonlinear controller.

Nonetheless, among the traditional controllers, a particular type has become very common for STATCOM implementations; the proportional integral (PI) controller. This has been widely used due to its simplicity and good performance. The PI controller is a simplified version of the proportional integral and derivative controller. Given that power systems are higly complex systems, the process of tuning these controllers is addressed under the assumption that the system's behaviour is partially unknown. Therefore, these controllers are usually tuned in a conservative manner. On the one hand, they are usually set to have a relatively slow response. On the other hand, the Derivative part of the original proportional integral and derivative controller is frequently cancelled.

Recently, modified versions of the PI controller, some of them including artificial intelligence, have been proposed. In [22], an adaptive PI controller is presented to provide voltage regulation using STATCOMs. Using this approach, PI controller parameters are automatically computed so as to ensure a desired response to every disturbance. In [23], the performance of three different controllers is compared for voltage regulation. In particular, a PI controller is compared to a pole placement controller and a linear quadratic regulator. The later showed the best performance, specially in case of extreme loading conditions. The PI controller performed in a similar manner to the linear quadratic regulator in normal loading conditions, but could not avoid unacceptable voltage values in stress situations. Additionally, AI-based methods have been also used to tune STATCOM's controllers. In [24], a tuning method for PI controllers for voltage regulation using STATCOMs is proposed. The proposed procedure uses GA, artificial neural networks and adaptive neuro-fuzzy inference systems for overcoming uncertainty in load dynamics.

On the other hand, the implementation of phasor measurement units (PMUs) in power systems has enabled researchers to take a step forward in the control of STATCOMs and other devices. PMUs provide time-stamped magnitude and phase angle of voltage and currents in real time. This enables SCADA systems to know in real time the behaviour and status of power systems. In [111], an AI based controller based on PMU data is presented. By concentrating real time data in a phasor data concentrator, using big data techniques, real-time operation of distributed FACTS may be performed in a fast and efficient manner. Similarly, a wide-area coordinating neurocontrol is proposed in [112]. This is based in wide-area coordinating control, which is enabled by the use of PMUs. The authors have developed a neural-network based wide-area coordinating control to coordinate control actions of different devices. Power system stabilizers, a large wind farm and multiple FACTS devices (SSSC and STATCOMs) were coordinated through this method. This approach enables an off-line training of the wide-area coordinating neurocontrol prior to its implementation. The proposed solution has led to a significant reduction in power oscillations in all generators within the power system.

The design and tuning of STATCOMs' controllers have evolved in parallel with both computing techniques and power system data management methods. In this sense, new computing and optimization techniques, such as artificial neural networks, genetic algorithms or particle swarm optimization, have been applied to these issues. At the same time, the development of PMUs and the enhancement of the data acquisition systems in power systems have allowed for more elaborated control solutions.

Nevertheless, tuning methods for FACTS devices' voltage controllers are usually focused on dynamic control parameters. On the other hand, impact assessment techniques usually consider their placement, sizing and optimal type [8]. However, it is also important to evaluate the effect of voltage control reference on the device's performance.

As argued in chapter 2.1, a proper power systems operation has to establish and accomplish adequate voltage values at the control buses. Voltage controllers are provided with voltage consigns by the transmission system operator. These consigns are set by voltage security constrained power flow calculations based on demand and renewable generation forecasts and generation dispatch, despite being based on techno-economical or market tools. However, voltage controllers are usually set with a concrete voltage control reference. That consign is changed only if necessary and frequently by non-automated methods.

As a part of the reactive power management system, FACTS devices need to comply with such requirements. In particular, they have to ensure a specific voltage on their reference bus. Thus, it is crucial to adequately select the voltage controller's reference value. Voltage reference values may be optimised for maximising voltage stability, minimising transmission losses or, in most cases, both of them. The optimal controller's reference value selection is thus a multi-objective problem focused on power systems stability and efficiency. Therefore, it may be addressed using the same techniques used for FACTS devices impact assessment, which have been described in this chapter.

As for FACTS devices placement, the optimal control reference selection will depend on the power system's conditions. The need for reactive power may vary as long demand and renewable generation power varies. Additionally, changes of the grid's topology may also affect the compensation requirements. Therefore, the voltage control reference value may be affected by demand variations, as well as other variables. Consequently, it is important to assess these interactions so as to ensure a robust reference value selection for voltage control based on FACTS devices.

Chapter 3

The Problem of Demand Variation

At first glance, power system load seems to be a stochastic variable which is function of multiple other variables, and in fact it is. From a transmission system operator's (TSO) point of view, load is better understood in terms of power demand, which is the compound load of several electrical devices owned by several customers [113]. Consequently, demand is strongly related to economical activities, social behaviour and environmental conditions. Human beings tend to turn activities into routines, so electric demand, as a consequence of human activity, behaves according to patterns.

As one would expect, this patterns change day to day, month to month and year to year, but the range of values they can take is restricted by human routines. It is unlikely that maximum and minimum demand change drastically from one year to another. That is why the ”peak/valley” method has long been widely used for planning studies. Indeed, it is very likely that demand will remain among expected peak and valley values throughout the year.

In power system planning studies, simulations are used to evaluate power systems performance. Models and input data are intended to represent the actual behaviour of loads and generators. In addition to guaranteeing security of supply, an important role of transmission systems is allowing for the optimal use of available generators. Thus, they ought to permit supplying loads from the most economical sources and operating generating units flexibly so as to improve reliability. It is important to note that power flows through transmission systems are directly related to generation dispatch, since transmission systems have very limited ability to control line flows [114]. Load distribution influences line flows, and generation dispatch is greatly influenced by the amount of demanded power. Therefore it is important to understand power system demand and to adequately model it.

Historically, power system analysis have been performed using deterministic load flow in ”extreme cases” scenarios, based on demand forecasts. Nonetheless, there is no generally-accepted forecasting model and the selected model will depend on the specific power system and its characteristics. Examples of these include the time-frame needed, the time resolution, the size of the area and the available data [115]. In fact, energy forecasting models are usually designed according to the particularities of the country or utility of interest [116].

In power system operation studies, short-term forecasts of demand are carried out. For every (operative) day, demand is forecast in fractions of an hour, half an hour or even 10 minutes to perform different simulations that emulate the concrete behaviour of all elements in a power system. According to the review carried out in [115], short-term predictions are usually based on historical demand data and environmental variables. On the other hand, power system expansion planning relies on long-term demand forecasts that are based on forecasts of socio-economic variables as well as historical demand data [115]. Long-term technological and political determinants may be also considered. The expected demand is derived from these forecasts based on the correlation between historical data of gross domestic product, energy price or population and demand data [116]. The result is usually one or more ”peak” demand values that serve as a representation of the worst-case operation scenario, considering its sensitivity to changes in the underlying predictions. Eventually, ”valley” scenarios may also be considered. In recent years, renewable generation scenarios have commonly been superimposed to demand scenarios to take this technology into consideration. This is the case of the Spanish transmission network expansion plan, which can be found in [117].

Therefore, the approach used in planning studies relies on the assumption of ”peak” demand as the worst case scenario, which leads to a constant and generalized oversizing of the generation and transmission facilities. It is worth noting that ”peak” demand is usually enlarged by a given percentage so as to assume the uncertainty of the results; for instance, in [117], peak demand is enlarged by a 10%. Furthermore, given that demand from different areas of a power system may behave differently, planning results may be affected in different ways. On the one hand, a dangerous situation in terms of stability may occur in an ”off-peak” operation situation. On the other hand, congestions, overloads and voltage issues may occur in different areas of the system depending on loading conditions. Consequently, the worst case scenario represents an appropriate approach to power system expansion planning as long as it is acceptable to oversize the system to tackle uncertainty. In contrast, we consider that a more detailed modelling of demand in planning studies may lead to less uncertain results and a reduction of the size of the facilities, maintaining the required levels of security.

Recently, the expansion of renewable unmanageable generators has added more uncertainty to power systems operation and analysis. Given that these generators cannot assure a certain amount of power at a certain future time, they cannot be included in power dispatch. Consequently, their power is usually subtracted from demand to form the net demand [114]. In such a context, the interactions between demand and renewable generation need to be taken into account and, thus, demand needs to be modelled more precisely. This further calls into question the traditional ”peak/valley” scope of power systems analysis, given that the deterministic approach lacks a significant amount of information about the load's behaviour [118]. For instance, in [26], the authors have demonstrated that variations in demand and renewable generation may condition the results of FACTS devices placement procedures.

Additionally, the emergence of new control devices, with increasing complexity, makes it necessary to evaluate not only the effectiveness of a certain operation strategy, but to look for the best one [119]. These complexities lead to the need for a wider scope on planning studies, designed to emulate real power systems operation so as to include the multiple scenarios that may occur. In these scenarios, both demand and unmanageable generators behaviour take part, as well as control and flexibility devices' behaviour. An efficient planning tool needs to take these aspects into consideration.

The appearance of disaggregated operation and control spaces, and the use of enhanced measurement systems and intelligence, will allow for the development of new planning tools, which will still be dependent on demand and generation forecast. This disaggregated environment makes it more difficult to make estimations. One reason for this is that, due to the effect of aggregation, traditional system-wide load curves are smoother and more predictable than those from smaller aggregations such as buildings, micro-grids or substations [120]. However, the vast majority of demand forecasting studies are designed to make predictions for large geographical areas.

For these reasons, a more detailed modelling of both demand and renewable generation is needed to ensure an adequate results of transmission system expansion planning studies in modern power systems. In this regard, demand models, as well as RES generation models, need to comply with two main features: they must be representative of the actual behaviour of the variable, and they must permit representing future situations. In other words, so as to guarantee robust results in power system expansion planning studies, we need predictive models that enable us to generate representative demand scenarios based on historical data, at the same time that they enable us to make predictions. In this section, an overview on how power system demand works, and how it is modelled in planning studies, is presented.

3.1 How Power System Demand Works

As mentioned before, electrical demand is the aggregation of consumption incurred by multiple agents: from people doing household chores to machines controlled by autonomous systems in factories. However you look at it, electrical demand is strongly related to human activities.

In 1920, Millar stated that, traditionally, people's choice of sleeping hours seemed to coincide with the hours of colder temperatures [121]. This is probably due to the fact that being in a cosy bed makes it easier to keep warm in winter. In summer, people often prefer to wait until temperatures drop before they go to bed. The author pointed out that, at the same time, people had to reserve suitable hours for work and leisure. He added that old customs tend to persist and societies seem to have reached an arrangement ivolving comfortable temperatures and light conditions when organising their daily life.

Time has passed and new technologies have entered people's lives and, as result, electrical consumption. Nevertheless, the underlying effect of human customs remains. For instance, the heating and cooling of building has become part of electrical demand in industrialised societies. Nevertheless, decisions about how to use cooling or heating are influenced by a similar determinant: the temperature at the time the decision of whether to use this service or not is made [122].

Therefore, electrical demand follows patterns which are related to people's vital and economic cycles. In industrialised societies, human activities are firmly conditioned by the organization of people's lives according to working days in particular, and to economic activity in general. These patterns may be classified as economic or environmental. On the one hand, economic patterns reflect changes in people's activities derived from their production tasks. Every kind of production activity has its own production cycle and, hence, its own particular demand pattern. Furthermore, a clear distinction may be made between working days and holiday/weekend days. On the other hand, environmental patterns are a consequence of changes in human activities produced by the environmental conditions. Changes in the daylight hours and meteorological conditions greatly affect people's routines.

Different time scales may be used for studying electrical demand and different temporal patterns may emerge from these scopes. The most intuitive and smallest time scale in which patterns may be found is the day. However, environmental conditions follow their own cycle during the year, so months or seasons may be used to account for these variations. Differences and similarities may be found in electrical demand during different seasons on a weekly scale. Therefore, weekly demand patterns may be useful for abstracting particular day to day variations and representing monthly/seasonal behaviour. Occasionally, annual patterns may also be used.

In figure 3.1, hourly demand data of the El Hierro island power system [123] can be found. The weekly time series clearly shows the daily pattern of electrical demand, and how it changes depending on whether it is a weekday or weekend, and depending on the time of the year.

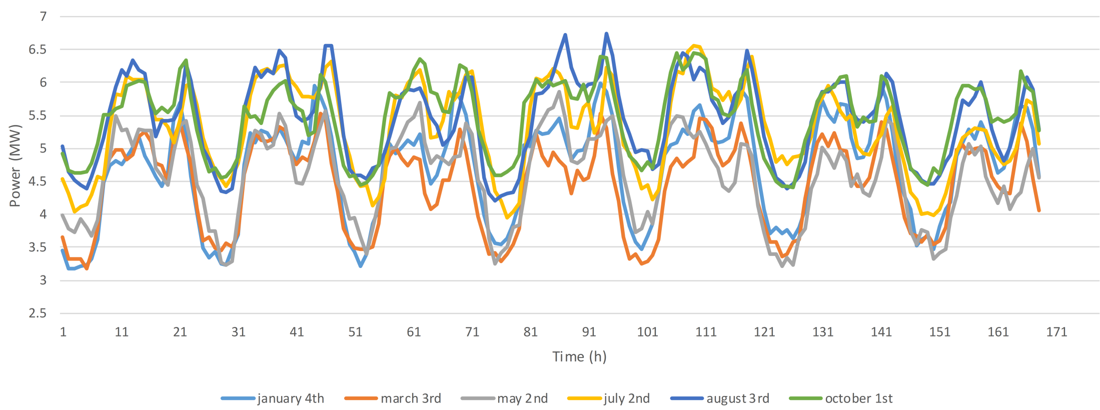

Figure 3.1: Hourly electrical demand of El Hierro island (Canary Islands, Spain) for different weeks.

The idea of electrical demand as an aggregation of loads can be applied at both consumer and substation level. In fact, system demand is an aggregation of demand from several substations. Demand from different substations behaves in different ways [124], so load share between them may also change in time. Once more, changes in load share will depend on, and be restricted by, routines and habits of people from different areas within a power system. In figure 3.2, geographically distributed data of hourly demand for a period of one year [125] is shown for 13 substations. Data is represented in terms of total power of each demand scenario and load share of every substation for each scenario. Thus, for every hour or the entire year, a set of n points is plotted in the chart, n being the number of load buses, which is 13 in this case. The points corresponding to the same demand scenario share the same y coordinate, which represents the total amount of demanded power. The x coordinate represents the share of the total demand (for that particular scenario) that corresponds to every individual bus as a percentage, the load share.

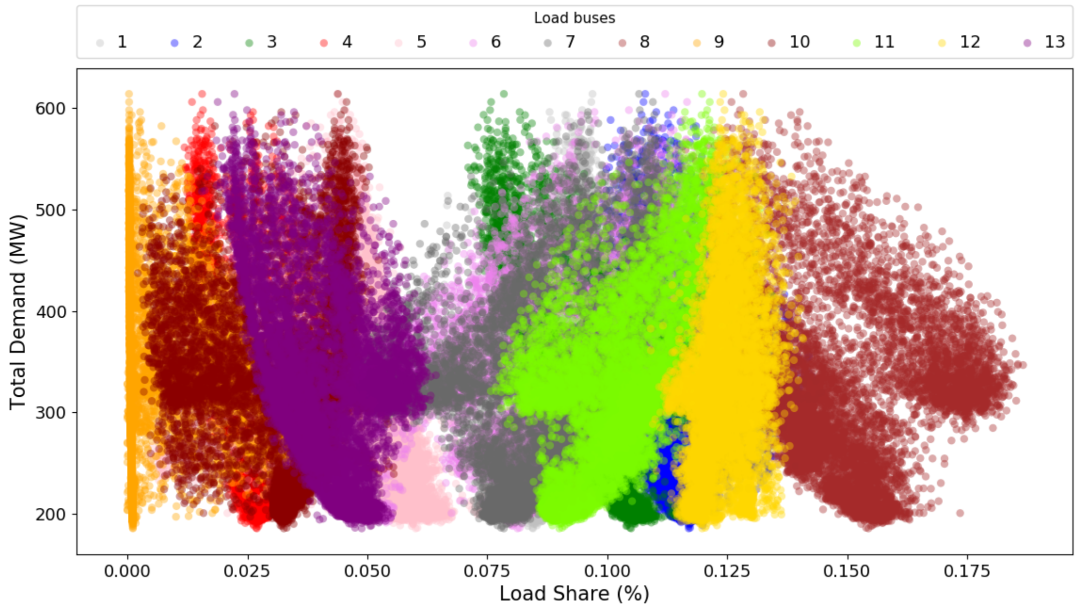

Figure 3.2: Demand data as a function of total power and load share.

3.2 Power System Demand Modelling Issues

In order to characterize electric demand, from a transmission systems expansion planning perspective, different sources may be used. From a qualitative point of view, a description of the determinants affecting power systems demand is performed in [121]. From a quantitative point of view, TSOs and researchers have developed different approaches.

TSOs provide periodical information about electrical demand. For instance, the Spanish TSO publishes monthly demand reports including aggregated values of daily demand at a system level [126]. Furthermore, detailed system annual demand data is published including peak and valley demand values, demand variation, demand modelling variables such as temperature or gross domestic product and peak daily demand profiles [127]. The National Grid Energy System Operator of the United Kingdom publishes hourly aggregated data for demand, generation, storage, pumping and international transactions of power every year [128]. Similarly, hourly demand and generation data of the Spanish power systems may be found in [123]. Unfortunately, these two approaches give us an example of the existing situation in terms of demand data availability for planning purposes. Traditionally, demand data has been provided in a highly aggregated manner since only daily, monthly or annual power system demand was provided. Recently, TSOs have provided more time disaggregated data, providing hourly data of power systems every year. However, geographically distributed data, as well as reduced representative data sets, is still nearly unavailable.

Alternatively, different approaches have been used to find reduced representative data sets. The majority of them share a common feature, they are based on load profiles (LPs). LPs are estimates of the energy demanded by a group of loads over a specific period of time [129].

The Spanish TSO publishes annual load profiles based on the type of electrical supply contract [130]. However, this approach does not convey a meaningful classification of electrical loads since specifying the type of contract does not provide enough information about the kind of consumer involved. Similarly, in 2012, the Office of Gas and Electricity Markets of the United Kingdom published a study in which sectorial load profiles were calculated for non-domestic consumers [131]. Meaningful and useful load profiles were created and published, and this became a powerful tool for understanding power demand. However, this single-time initiative does not provide a foundation for demand modelling based on load profiles, since it cannot be used to predict future demand. A highly detailed study on domestic electricity use is presented in [132]. Domestic load profiles were calculated and interactions between different characteristics of the households and their load profile were found. The influence of income, home surface area, number of bedrooms, age and location (city, town, village or country) was studied. However, this was again a single-time initiative whose representativeness was limited, since the energy survey included only 27 households.

Researchers have also come up with an intensive study to provide reduced representative demand data sets. In [133] load profiles for residential, commercial and industrial low voltage consumers are calculated by aggregation of load profiles of the same kind. Mean and standard deviation of daily profiles are calculated for surveyed consumers to elaborate representative load profiles. In [124], a methodology for load forecasting, profile identification and customer segmentation, based on 245 time series of different high-voltage and low-voltage substations, is presented. Differences between demand behaviour from different substations are verified, even in terms of its sensibility to temperature. Principal component analysis and K-means clustering method were used to find representative load profiles from the different substation data. Given that there was no previous knowledge about the ”nature” of the electrical consumption from every substation, the results were interpreted by experts, who tried to assimilate every load profile to a traditional ”sectorial” demand behaviour. In [134] a detailed stochastic bottom-up model for domestic load profile elaboration is presented. This approach includes the modeling of different appliances such as lighting, cooking, laundry, etc. as well as the correlation between their duration and their starting time. Furthermore, social and economic factors, weekdays and weekend days and seasonal user patterns are taken into consideration.

A common feature of these studies is that they are all developed in collaboration with an utility company, which provided the necessary data. However, for the general scientific community, data sets with time and geographically distributed data are very difficult to find. More importantly, although these approaches are intended to create different kinds of descriptive models for demand, few works have been found in relation to predictive models and their implementation for demand scenarios creation.

As previously mentioned, the increase of non-manageable renewable power and the more active role played by customers have increased uncertainty in power systems operation and analysis. This situation leads to the need for considering more demand scenarios in planning studies. When several demand scenarios are taken into account, three methods are commonly used; namely, Monte Carlo simulation, load profiles and historical data. These methods are described below, paying special attention to the aforementioned requisites for a demand model; representativeness of the actual demand behaviour and capability of representing future demand.

3.2.1 Monte Carlo Simulation

One of the most frequent demand modelling methods is the Monte Carlo simulation (MCS) method. MCS is a stochastic simulation technique that serves for analyzing random processes, but also some time dependent processes [135]. The MCS method consists of randomly creating a sufficient amount of scenarios, following a given probability density function (PDF). By doing so, the individual behaviour of every single variable may be represented more or less completely depending on the number of scenarios. After estimating, or assuming, a probability density function for electrical demand, it may be simulated by using MCS.

The MCS method has been used for FACTS devices placement from both technical [26] and economic [136] perspectives. Similarly, it has been used for distributed generators placement [137] and flexibility sources planning [138]. In all cases, the MCS is intended to account for the variability of demand and non-manageable generation. Furthermore, the MCS has been also used as a basis for probabilistic power flow calculation in different studies ([139], [140] and [141]).

Since MCS is based on PDFs, it is enabled to model the future behaviour of power system demand. Nonetheless, given that values for every variable are generated randomly, the patterns resulting from demand and other power system variables, such as photovoltaic generation, may not be preserved. Moreover, the effect produced by the interactions between patterns of two or more variables may also be disregarded. Consequently, MCS might not always ensure the representativeness of the results. Although common statistical software includes a wide range of random sample generation tools, they commonly generate independent samples, so additional methods are needed to generate correlated samples [142].

One of the concerns of this work is to address the variations of demand geographical distribution. By randomly generating demand values for every substation, attending to their own probability distribution, geographically distributed demand scenarios may be generated. However, if MCS was used for this purpose, the interactions between demand patterns of different substations may not be taken into consideration. To obviate these interactions may also harm the representativeness of power system planning studies. In [142], the authors propose a solution to probabilistic load flow calculation considering the correlation between groups of loads and generators. In order to compare their results, they developed a method to create correlated samples using MCS based on the normal to anything process. This method included different rules and constraints so as to ”guide” the scenarios creation process and provided good results for load and wind power scenario creation with normal and Weibull distributions, respectively. Nonetheless, this method failed to represent solar power data due to the presence of a great number of zeros corresponding to night-time values. In this case, historical data was used to represent photovoltaic generation.

A combined solution to ensure the representativeness of power system analysis is proposed in [143]. The proposed methodology is based on LPs and a constrained MCS procedure for distributed generators (DGs) modelling. Before the process is started, load profiles for residential, commercial and industrial load characteristics are defined in terms of load scaling factors. In addition, load buses are classified as residential, commercial and industrial buses so as to model their behaviour. After that, the process is started and the number of ”on state” DGs and their location, as well as the DG power, are randomly created. Depending on the test being performed, these scenarios may be filtered so as to respect a maximum aggregated DG power penetration. Thermal and stability constraints are also included to obviate unfeasible PF calculations. DG scenarios are created, for every hour of the day, based on a fixed load scenario, until a converged power flow (PF) calculation, that complies with the constraints, is found. Using this approach, a statistical representation of distributed generation may be achieved. The authors use two kinds of constraints to model the cyclic component of DGs power. Firstly, they limit the range of values that the power of every DG may take, in relation to its rated power, depending on the hour of the day. Consequently, a step-wise cyclic component is superimposed on individual DG behaviour. Secondly, in some of the studies, the DG penetration is limited to 15, 25 or 35% of demand so as to reproduce the limitations that TSO may impose on DGs. However, some issues may limit the effectiveness of this approach to ensure the representativeness of demand scenarios. Firstly, only 24 geographically disaggregated demand scenarios are comprised. Additionally, each load bus is supposed to be represented by some of the sectorial load profiles (residential, commercial and industrial) rather than by a combination of them.

3.2.2 Load Profiles

The load modelling method based on load profiles (LPs) may address the difficulties related to power system demand representativeness. This method consists of creating a number of estimates of the energy demanded by a group of loads over a specific period of time [129]. In most cases, these estimates are daily load profiles from which load scenarios derive. Some load scenarios may be extracted directly from load profiles, but a great number of scenarios may also be created through different procedures.

As mentioned before, some TSOs have provided different kinds of LPs. The Spanish TSO provides LPs based on the different types of electricity supply contracts [130]. Nonetheless, the aim of these LPs is only to provide hourly data from monthly energy consumption for billing purposes. These LPs are in fact a set of coefficients from which every pseudo-sectorial LP is extracted. By multiplying the given coefficients by the amount of energy measured during a billing period (one month), the estimated LP is calculated. Using a different approach, the Energy System Operator of the United Kingdom published a set of sectorial LPs based on a survey [131]. This is a bottom-up approach in which sectorial LPs are accompanied by a set of coefficients that enable producing a year's worth of hourly scenarios for every productive sector. The addition of the different sectorial sets of scenarios would compose the aggregated demand. Similarly, the Institute of Electrical and Electronics Engineering has published a procedure for demand scenarios creation based on load profiles [144]. LPs are defined, for every season, week and weekend days. The corresponding LPs have to be multiplied by a given coefficient, depending on the time of the week during a year and the corresponding day of the week. By doing so, daily LPs are created, composing a set of hourly scenarios to simulate an entire year of electrical demand.

LPs extraction have been widely studied by researchers for decades. For instance, clustering methods, in combination with probabilistic artificial neural networks, have been used to group consumption time-series from anonymous consumers into load profiles in order to improve market tools in [145] and [146]. The K-means clustering method has been used to extract representative LPs for electrical load associated with water distribution systems [147]. In [148], sectorial LPs for industrial, commercial and residential customer groups are calculated. The aggregated LP of the studied power system is calculated from the sectorial LPs. This approach implicitly models net demand based on LPs, since the same probabilistic neural network is trained to derive a generation profile for a wind power plant from wind speed data. In [133], statistical analysis has also been applied to characterise residential, commercial and industrial LPs of consumers in distribution networks. A probabilistic approach is proposed in [134] for domestic LPs modelling.

Given the great amount of data needed for these approaches, data compression techniques have been applied to LP extraction. Thus, hourly LPs have been transformed into frequency domain by Fourier transform in [149] and [150] prior to the clustering procedure. A specific application of direct Fourier transform for annual LPs is presented in [151]. A comparison between discrete Fourier transform and discrete wavelet transform for dimensionality reduction is presented in [152].

It is important to note that the approaches referred to are limited to representing ”past” demand, since LPs are derived from historical data. Moreover, in general, the authors do not describe methods for generating future demand scenarios based on LPs. In such a situation, a temptation to use linear extrapolation or interpolation may exist. However, this approach would undermine the implications of new electrification technologies, as stated in [153]. To deal with long-term demand dynamics, the authors propose a comprehensive tool for long-term energy demand/supply modelling. This tool generates LPs endogenously based on the characterisation of different demand technologies and fuel options available in the model. The model also optimises the energy supply at the lowest cost using an hourly representation of weekdays and weekends from three seasons with a long time horizon. Cross-sectorial interactions and competition for the allocation of energy carriers are also considered.

Additionally, LPs based exclusively in overall electricity demand may not properly represent seasonal variations in the shape of LPs, as proved in [133]. The authors compared synthetic LPs with monitored LPs and found discrepancies in monthly variations of load factors in timing of daily peak loads. To avoid inconsistencies in LPs representativeness, the authors recommend considering multiple characteristics of load profile shapes.

Therefore, LP comply with both stated requisites, they respect the coincidences of different demand patterns and they may also represent future situations. However, although a great work has been done in classifying demand patterns as load profiles, little has been done in building demand scenarios from load profiles [129]. In the cited paper, the authors account for the variations that occurred in power system variables due to demand variations derived from a single aggregated LP. In [154] a method is presented to build composite standard load profiles based on standard load profiles representing different low voltage customer types. These composite LPs are validated by calculating symmetric mean average percentage error between them and the real load profiles. However, real LPs were constructed by aggregating LPs of only 45 households. Another very interesting approach is presented in [155]. The authors use multiple Gaussian functions as a method for creating domestic LPs based on the number of households and other socio-economic variables. This study is based on LPs and sensibilities provided in [132] from a survey of only 27 households. Consequently, in this brief review we have found that simulation-ready LPs barely exist and, when they do, it is difficult to assess their actual representativeness.

Finally, a comment on LPs and geographically disaggregated demand representation needs to be made. If electrical demand is understood as an aggregation of a great number of consumptions/loads, different aggregations are enabled. A functional aggregation may be then stated, classifying loads in accordance to the ”human activity” they derive from. Nonetheless, spatial aggregations are also interesting for power system analysis. LPs may permit such a modelling method, enabling a time and geographical disaggregation of demand. By doing so, electrical demand for different power systems' areas may be characterized, for instance, at a substation level. Although the aforementioned methods may reflect the coincidences of different demand patterns, they are intended to provide a unique distribution of the aggregated demand of a particular power system, disregarding the effect of variations in load share. However, the development of such a methodology is beyond the scope of this work.

3.2.3 Historical Data

Despite the aforementioned resources, the use of historical data is not a common option in research works. As previously mentioned, TSOs used to provide highly aggregated data, but they are now publishing hourly demand data ([123] and [128]), usually from year to year. However, different issues may emerge from the use of such data in power system expansion planning studies. Additionally, demand data provided by TSOs is very frequently limited to system-wide power, so geographically disaggregated approaches are hindered by this fact. A few sources of geographically distributed demand data have been found ([125] and [156]).

Historical data providing detailed information of power systems demand reflects the coincidences of patterns of different variables, since they are time series. Nonetheless, this kind of data cannot be reliably used to represent future situations [153]. As mentioned before, the use of extrapolation to represent demand growth may not provide robust results. Even if more sophisticated approaches are implemented, such as the autoregressive integrated moving average method, changes in load shape derived from new habits or technologies may not be assessed. In [157], this method is used to forecast long-term aggregated demand growth based on historical data. However, no distributed scenarios are created, nor are demand patterns considered, since only the mean per capita energy consumption is used. In [158] a demand response model for residential appliances is presented. The model uses the autoregressive integrated moving average method to construct basic LPs which are finally modified to account for specific appliances. Air conditioners, water heaters, electric vehicles, photovoltaic systems and demand response strategies are specifically modelled using different methods.

In addition, using historical data, the representativeness of the demand data is only guaranteed for the power system from which data was measured. Cultural differences, as well as environmental aspects, such as daylight hours, and the use of different technologies, such as cooling or heating systems, may substantially modify the shape of demand patterns from one country to another. Differences may be found even within the same country. Thus, demand data from a given power system cannot be used to create representative demand scenarios to be simulated in a different power system model. This is especially important if one is thinking of studying demand variations in a power system for which distributed demand data is not available.

3.3 Conclusions

As mentioned before, a satisfactory modelling technique for representing geographically disaggregated power system demand, respecting the coincidences of different patterns, has not been found. On the one hand, MCS does not inherently account for these patterns. On the other hand, demand data sets based on LPs have been found, but they do not provide geographically distributed data. Some approaches have confronted these issues independently, but with the cost of complicated and data intensive solutions. Finally, historical substation demand data sets have been found, but they cannot represent future situations and they are unambiguously related to a specific power system.

It is beyond the scope of this work to develop a demand modelling procedure, thus one of the existing methods needs to be used. One of the main concerns of this study is to account for interactions between demand from different substations, therefore MCS was discarded. In addition, LPs were rejected because a systematic manner to represent distributed data could not be found. Consequently, historical distributed data from [125] was used. This data was assessed to adapt the benchmark power system used for testing.

Chapter 4

Hypotheses

This chapter is intended to present and describe the main hypotheses on which this research is based. As discussed earlier, FACTS devices impact assessment may be influenced by demand variations in terms of total power and load share. Distributed data coming from different system nodes or substations may enhance the results obtained from these studies.

In its simplest form, the FACTS device allocation can be reduced to a single phase line compensation problem, since a loss-less power line with distributed parameters is ruled by equations 4.1 and 4.2 [4].

$$V_x = V_R * cos(\beta * x) + j * Z_C * I_R * sin(\beta * x) \tag{4.1}$$

$$I_x = I_R * cos(\beta * x) + j * V_R / Z_C * sin(\beta * x) \tag{4.2}$$

Where V_x and I_x represent voltage and current at a distance x from the sending end of the line, β is the *phase constant* of the electrical wave, V_R and I_R represent voltage and current at the receiving end, and Z_C is the *characteristic impedance* of the line.

On the one hand, if we substitute x by the length of the line (L) we can calculate voltage and current at the sending end. Which means that $V_x = V_S$ and $I_x = I_S$. On the other hand, if a voltage source is connected to the sending end of the line and the receiving end is open-circuited, the current at the receiving end is $I_R = 0$, and the voltage at the receiving end is much higher than at the sending end, $V_R >> V_S$. Nevertheless, if we close the line with its Z_C , its voltage and current magnitudes remain constant along its length (*flat line*) [4], since its reactance is compensated.

When the line is connected to sources of identical voltage in both ends, $V_S = V_R$ and $I_S = -I_R$, since both currents are entering the line. Hence, following the principle of symmetry, the current must become zero at half the length of the line ($x = L/2$). In such a situation, we can treat each half of the line as an open-circuited line. Consequently, a loss-less power line connected to identical voltage sources in both ends may be compensated by half of its Z_C at its midpoint.

Given this context, we tried to figure out if the *theoretical point of compensation* may move along the line as long as its loading conditions are changing. According to eq. 4.2, if $I_x = 0$ we can calculate x, which represents the point in which a line fed by both ends may be compensated.

With this in mind, we built a model (Fig. 4.1) that emulates a power line connected to identical voltage sources at both ends via shunt impedances ($d * Z_{Ld}$ and $(1-d) * Z_{Ld}$). If $d = 0.5$, shunt impedances at both ends of the line are equal. Hence, $V_S = V_R$ and $I_x = 0$ at $x = L/2$. In contrast, if $d \neq 0.5$, shunt impedances are not equal, $V_S \neq V_R$ and $I_x = 0$ at $x \neq L/2$. In other words, depending on the balance of load at both ends of the line, the theoretical point of compensation may take different positions along the line following a linear relationship.

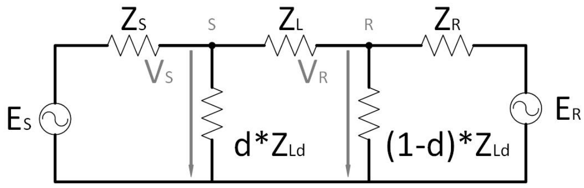

Figure 4.1: Modified power line model.

Finally, we can generalise the problem to n lines by generalizing equations 4.1 and 4.2 and making the aforementioned assumptions (eq. 4.3 and 4.4).

$$V_x^{ik} = V_k * cos(\beta_{ik} * x_{ik}) + jZ_C^{ik} * I_{ik} * sin(\beta_{ik} * x_{ik}) \tag{4.3}$$

$$I_x^{ik} = I_{ik} * cos(\beta_{ik} * x_{ik}) + jV_k/Z_C^{ik} * sin(\beta_{ik} * x_{ik}) = 0 \tag{4.4}$$

Where i and k are nodes linked by the line whose parameters are denoted with ik.

In conclusion, it can be mathematically proved that: *a)* the position of the theoretical point of compensation depends on the loading condition of the line, *b)* this can be generalized to the n lines of a power system. Hence, the optimal placement for a compensator within a power system may change depending on the load share. For this reason, if we intend to look for an optimal placement for any kind of compensator, we shall take into account as much load share scenarios as possible.

4.1 Hypothesis on FACTS Devices Placement Considering Distributed Data.

Simulations are widely used for power systems performance assessment. In such studies, models and input data are supposed to represent the actual behaviour of loads and generators, while the power network is usually treated as a ”passive” element. Given that generators characteristics and dispatch rules are common for every simulation, demand will be the determinant variable to create different operation scenarios. Depending on the amount and distribution of the demand, the reaction of the generators will differ and the distribution of power flows and bus voltages will change. Nonetheless, it is important to note that demand variations occur not only in their aggregated value, but as a consequence of the sum of load several electrical devices aggregated in different substations. Therefore, to adequately model electrical demand, a time and space disaggregated scope needs to be used.

On the other hand, the expansion of variable renewable generators has increased uncertainty in power systems operation and analysis. In such a context, the interactions between demand and renewable generation needs to be taken into account and, thus, demand needs to be modelled more precisely. This questions the suitability of the traditional approach in which predefined worst-case scenarios (usually peak and valley) are used to represent power system operation.

Additionally, the emergence of new control devices, with increasing capabilities, makes it necessary to look for the best possible strategy instead of just evaluating the effectiveness of a certain operation strategy [119]. These new complexities lead to the need for a wider scope on planning studies, intended to emulate real power systems operation, considering the multiple scenarios that may occur. In these scenarios, both demand and renewable unmanageable generators take part, as well as control and flexibility devices. An efficient planning tool needs to take this aspects into consideration.

As stated in [26], the presence of some types of renewable generators may have an important effect on FACTS devices placement results. Therefore, the impact of FACTS devices may not be adequately assessed if operation scenarios are not properly selected. In particular, the number and configuration of demand scenarios is crucial. The authors have noted an inconsistency with classical methodologies, since they have demonstrated that peak scenario may not ensure the optimal solution and thus it is not always the best system configuration for running a FACTS placement procedure.

Nonetheless, most of FACTS devices placement procedures found in the literature do not take load variations into account. Changes in loading conditions, particularly loading level and load share, may affect the results of these studies. This is especially true in the presence of renewable generators providing stochastic power. Therefore, there is a need for procedures that consider these interactions so as to provide robust results in the context of restructured market-oriented and small isolated power systems.

In this document, a technique for optimally placing FACTS devices attending to load share is presented. The fundamental hypothesis of this research is that:

- **Hypothesis 1:** Considering a greater number of demand scenarios with a variable load share among the different buses may provide better results in FACTS devices placement studies.

In this context, load share is understood as the distribution of the aggregated power system load into the different system buses or substations.

4.2 Hypotheses on FACTS Devices Control Considering Distributed Data.

The design and tuning of FACTS controllers have evolved in parallel to both computing techniques and power system data management techniques. Consequently, new computing and optimization techniques, such as artificial neural networks, genetic algorithms or particle swarm optimization, have been used to design and tune controllers in a more effective manner. At the same time, the development of phasor measurement units and the enhancement of the data acquisition systems in power systems have allowed for more sophisticated control solutions.

Furthermore, it is worth emphasising that the impact of FACTS devices on power systems spreads from the point of connection to the surrounding area. Due to the nature of the power flows in power systems and their high interconnection, the effect of VAR compensation affects not only the bus to which the device is connected, but also its nearest buses.

In such a context, there is the opportunity to consider a wider approach in the control of FACTS devices. To this end, some clues have been found in different research works. In [89], a study on voltage control and reverse power flows mitigation is presented. From the different test performed in both the low and medium voltage sides of the power grid, voltage control is found to be more effective in low voltage feeders. In [83] a comparison between STATCOM and BESS for damping regulation is presented. The authors demonstrated that remote control signals showed better results than local signals for damping oscillations in STATCOM mode.

Consequently, given the implications of voltage control, and particularly voltage reference, on the performance of FACTS devices, it is important to optimally select a reference value for voltage control. As mentioned before, the effect of FACTS devices on power systems operation is influenced by other variables, in particular electrical demand. Thus, it is important to consider an adequate set of demand scenarios so as to ensure robust results.

In this research, different control signals have been evaluated to enhance the performance of a FACTS device's voltage control. Therefore, an optimally placed STATCOM have been configured so as to perform voltage control with different reference values. Historical distributed demand data has been used to create several demand scenarios in order to account for demand variations. This approach relies on two basic hypotheses:

- **Hypothesis 2:** The reference value influences the effectiveness of the voltage control performed by FACTS devices.

- **Hypothesis 3:** Considering a greater number of demand scenarios with a variable load share among the different buses may provide better results in FACTS devices configuration studies.

Chapter 5

Proposal

FACTS devices modify the impedance of the transmission grid's element to which they are connected in order to enhance power transmission. Therefore, they may improve power flow and voltage profile, as well as reduce power losses. However, power flows along transmission grids depend not only on the impedance of each element, but also on the general operative conditions, including demand and generation. Hence, in order to achieve a robust solution to the FACTS devices impact assessment problem, distributed data may be used so load variations are properly taken into account.

In this chapter, a methodology for FACTS devices impact assessment is described. This problem is stated as a multi-objective optimisation problem based on performance indices related to different operating variables coming from power flow (PF) calculations. Nonetheless, despite different power system's variables being commonly used for technical and economical assessment, the actual information they provide for this particular application is unclear. For this reason, different indices have been evaluated in terms of the statistical information they provide. Those providing the most complementary information have finally been selected for FACTS devices placement. With the aim of providing useful information for transmission expansion planning decision making, a Pareto optimality-based optimal placement method has been developed.

5.1 Simulation Procedure

In this section, the simulation procedure followed for FACTS devices placement and tuning is described. As previously mentioned, in order to guarantee the results' representativeness, a sufficient number of demand scenarios needs to be considered. Given the advantages and drawbacks of the different demand scenarios generation methods, historical hourly data has been used to represent an entire year of power system operation (see chapter 3).

Taking advantage of the historical distributed demand data set, and based on the benchmark power system's data, 8760 demand scenarios have been created. For each demand scenario, load values were updated and an optimal power flow (OPF) calculation was performed. Once the power flow was optimised, a P-V analysis was performed to the *base case* (without the FACTS device) and system variables were stored. Then, for each candidate solution, a FACTS device was set and configured, and a new OPF calculation was performed. Again, P-V analysis was used to evaluated the voltage stability margin of each simulation scenario and FACTS location/configuration. The flow diagram of this process is presented in figure B.1.

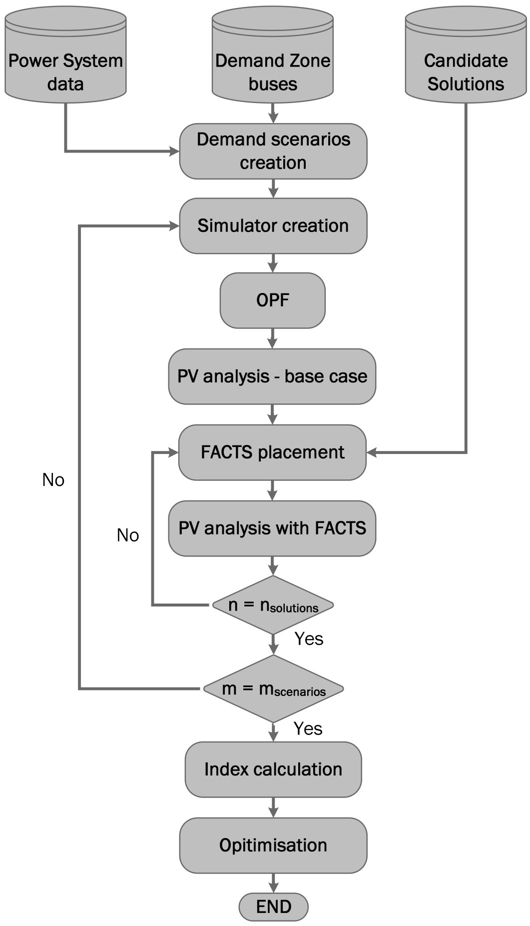

Figure 5.1: Simulation procedure flow chart.

5.2 Performance Indices

Once the simulations were carried out, different performance indices, based on the selected system variables, were calculated in order to evaluate the impact of the FACTS device. These indices have been selected to convey different aspects of power system operation from either a technical or economic point of view. From the literature review, it is clear that voltage stability indices are the most common, followed by transmission losses [9], while greenhouse gases emissions have been recently included into power transmission expansion planning studies [108].

Therefore, in this research 6 different indices have been used to assess FACTS devices impact on power systems. Firstly, three indices have been selected as a measure of voltage stability; these are loading margin (λ), voltage deviation (V_{dev}) and reactive power losses (Q_{loss}). After that, two indices have been included to assess power system's efficiency; namely, operation costs (C_{op}) and active power losses (P_{loss}). Finally, greenhouse gases emissions (E_{GHG}) have been added to evaluate the environmental implications of reactive compensation based on FACTS devices.

Loading margin (λ) is used as a measure of the system's voltage stability margin, since it measures the distance from actual loading conditions (P_{demand}) to voltage collapse (P_{max}).

$$\lambda = \frac{P_{max} - P_{demand}}{P_{demand}} \tag{5.1}$$

Voltage profile is also analysed as a means for voltage stability assessment. Therefore, voltage deviation may be used as a means of voltage profile 'flatness'. Voltage deviation may be stated so that:

$$V_{dev} = \sum_{bus=1}^{bus=n} \left| \frac{V_{rated} - V_{bus}}{V_{rated}} \right| \tag{5.2}$$

Where V_{rated} is the bus rated voltage (1.00 p.u) and V_{bus} is the actual bus voltage [101].

Voltage stability depends on the ability of power systems to meet the needs for reactive power. Therefore, reactive power loss may be used as a measure of voltage stability. When reactive power losses are low, needs for reactive power can be easily satisfied. On the contrary, when loading conditions approach to voltage instability, reactive power losses rapidly increase. Reactive power loss (Q_{loss}) may be computed as the sum of the reactive power losses of every branch (line or transformer) of the power system (Q_{brch}).

$$Q_{loss} = \sum_{k=1}^{k=n} Q_{brch} \tag{5.3}$$

Alternatively, active power loss can be used as a measure of system loading conditions or, inversely, as a measure of transmission efficiency. Active power losses are function of the electrical resistance of the transmission elements and the square of the current flow. The smaller the transmission capacity is, or the higher the transmission level is, the higher the active power losses are. Active power loss (P_{loss}) may be computed as the sum of the active power losses of all branches (line or transformer) of the power system (P_{brch}).

$$P_{loss} = \sum_{k=1}^{k=n} P_{brch} \tag{5.4}$$

Power systems operation costs may be also used as a measure of power system efficiency. These are generally divided in generation costs and transmission and distribution costs. Generation costs are usually determined by market mechanisms or merit-based procedures. In recent decades, market mechanisms have become a widespread solution to the electrical power dispatch problem. Nonetheless, in small isolated power systems, market mechanisms barely exist and generation costs are usually determined by assigning power to generating units according to their declared costs and computing the total incurred cost. From a system-wide perspective, transmission and distribution costs are usually calculated based on a transmission tax or fee, which is paid to the transmission/distribution utility for the use of the grid under its responsibility. In this work, distribution costs will not be considered, and only transmission costs will be calculated. Therefore, operation costs have been calculated as follows:

$$C_{op} = C_{gen} + C_{trans} \tag{5.5}$$

Generation costs have been estimated using a polynomial function based on the generated power [159].

$$C_{gen} = \sum_{i=1}^{n} a_i * P_i^2 + b_i * P_i + c_I \tag{5.6}$$

Where P_i is the power assigned to the ith generation unit at a certain dispatch period. Generation cost are calculated by adding the cost of the power provided by all generating units in operation at the studied dispatch period. a_i, b_i and c_i are coefficients that describe the relationship between output power and generation costs of every generator and, thus, they differ from one generation unit to another.

Transmission costs are estimated as follows:

$$C_{trans} = \tau * \sum_{i=1}^{n} P_i \tag{5.7}$$

Being τ the transmission fee in $\$/kWh$ and P_i the power provided by every one of the n generation units that participate in the generation dispatch at the studied dispatch period in kWh.

Finally, GHG emissions have been introduced in this analysis to account for environmental externalities of power system operation. According to [159], GHG emissions may be estimated in a similar manner than (5.6) so that:

$$E_{GHG} = \sum_{i=1}^{n} \alpha_i * P_i^2 + \beta_i * P_i + \gamma_i \tag{5.8}$$

Were α_i, β_i y γ_i are the coefficients that determine how each i generating units behaves in terms of GHG emissions according to its output power.

As previously mentioned, the main goal of this research is to evaluate the influence of load variations in FACTS devices impact assessment, and develop a methodology able to account for them. Thus, a large number of simulations, combining demand scenarios and device's locations, need to be evaluated (see figure B.1). However, the aforementioned indices are designed to convey a particular attribute of a concrete power system configuration. Consequently, a huge number of different values will emerge for every index from the simulations. For this reason, a method is proposed based on a unique measure of average power system behaviour regarding each of the selected indices.

Given that different locations must be compared, and several demand scenarios must be considered, performance indices must be treated so that a single quantity determines the quality of every possible solution. With this in mind, for every available location, performance indices have been normalized as a 'relative improvement' of the 'base case' situation, in which no FACTS device is involved. Furthermore, so as to take all demand scenarios into account, the mean value of the 'relative improvement' of every available location and index for all demand scenarios have been calculated.

The mean relative improvement (MRI) has been designed to enable the maximization of the different indices via Pareto optimality. Therefore, the *MRI*, for every index may be calculated as follows:

$$MRI_i = \frac{1}{n}\sum_{j=1}^{n}\frac{PI_{FACTS}^{i,j} - PI_{base}^{j}}{PI_{base}^{j}} \tag{5.9}$$

Where PI_{base}^{j} is the value of the performance index at the base case (without FACTS device) of the jth demand scenario and $PI_{FACTS}^{i,j}$ is the value of the performance index of the jth demand scenario when the FACTS device is implemented according to the ith candidate solution.

Nonetheless, most of indices (except from λ) need to be minimised. Given that the MRI needs to be maximised, the sign of the MRI related to these indices has been changed before they are minimised. The MRI related to these indices is computed as follows:

$$MRI_i = -\frac{1}{n}\sum_{j=1}^{n}\frac{PI_{FACTS}^{i,j} - PI_{base}^{j}}{PI_{base}^{j}} = \frac{1}{n}\sum_{j=1}^{n}\frac{PI_{base}^{j} - PI_{FACTS}^{i,j}}{PI_{base}^{j}} \tag{5.10}$$

5.3 Index Selection Based on Mutual Information

As mentioned before, performance indices for transmission expansion planning, and particularly for FACTS devices placement, are not commonly selected through systematic methods. Instead, they are frequently selected through methods that rely on decision-makers expertise. In this context, mutual information may be used for indices selection, providing a traceable method that may be generalised.

In this work, feature selection is used for index selection within the proposed FACTS devices placement procedure. In this context, the amount of information provided by the feature subset becomes relevant. The idea is then to include those indices which provide the most heterogeneous information or, in other words, those which are the most complementary. For this reason, the feature selection algorithm must search for the feature subset with the least MI between features. As mentioned before, the calculation of the MI between all features within the feature set may lead to an exponential computational burden, due to the number of feature combinations. Nonetheless, since the MI is computed for all feature combinations, it is possible to find an enhanced solution, given that the interdependencies between pairs of indices are taken into account.

The information theory approach allows us to formulate an heuristic algorithm in order to choose those indices which maximise the information accounted in the FACTS placement procedure. With this aim, we present an algorithm intended to search for the indices subset which has the most heterogeneous information. The algorithm is designed to discard those indices with the greatest shared information, which are those with a smaller $D-distance$.

It is important to note that D is a metric that link two variables (or indices) on an equal footing, given that it is symmetrical. Thus, once we have determined which two indices are the closest to each other, D does not allow us to decide which has to be eliminated. However, it is crucial to determine which indices have to be excluded and, at the same time, to preserve the remaining index so as to retain as much complementary information as possible. With this aim, the following variable selection procedure has been developed, attending to the particularities of this study.

In order to optimally assess FACTS devices impact, it is necessary to evaluate several candidate solutions, which provide complementary information about the problem; in the same way that different indices also provide heterogeneous information. For this reason, it is important to consider both determinants. For instance, in this work, 6 indices have been selected to evaluate the STATCOM's performance in 8 different locations. The $D-distance$ needs to be calculated for every combination of indices and for every available location, so a tridimensional distance matrix has been created. This distance matrix is composed of k bidimensional sub-matrices of the size $n*n$, k being the number of available locations and n the number of indices. Each of these sub-matrices is described as follows:

$$DM^k = \{D(I_i^k;I_j^k); i = 1...n, j = 1...n\} \tag{5.11}$$

Where i y j denote each index (I) within the index set (S) composed by n indices, and k represents each of the available locations within the set (L) of l locations.

It is important to mention that, given that the $D-distance$ is computed between each of the pre-selected indices, the distance matrix is symmetrical. Therefore, only the elements belonging to its upper triangular submatrix are computed. At the same time, the positions along the diagonal of the matrix are not computed either, since they represent the "self-dependence" of every index.

Nonetheless, a single measure of the complementary between every single index is needed in order to compare them. The "worst-case" criterion has been used to determine the importance of each index in terms of the information it provides to the study. Thus, the smaller value of the $D - distance$ associated with each combination of indices has been selected among the k values related to the different available locations. A bidimensional matrix has been created, comprising the smallest distances between every pair of indices so the indices may be selected as a function of their worst value. Consequently, indices sharing the least information may be selected based on the maximum information they proved to share. The reduced distance matrix, comprising a single value of distance for every combination of indices is constructed as follows:

$$DMr = DMr \cup \{\underset{k \in L}{argmax}(D(I_i^k; I_j^k))\} \tag{5.12}$$

Once the reduced distance matrix is computed, the following sequential elimination procedure is executed to select the sub-set of indices that provide the most complementary information:

1. Compute aggregated distance: for every index, the D distance respect to every other index is summed as a measure of its similarity to the whole set.

2. Choose a pair of ”nominated” indices: the pair of indices with a smaller D distance between them are selected as candidates to be excluded from the set.

3. Eliminate one index: among the ”nominated” indices, the one with the smallest aggregated distance is eliminated.

4. Repeat steps 2 and 3 until the size of the remaining subset of indices coincide with the desired size.

For the sake of clarity, the pseudo-code of the index selection algorithm is provided below.

```
for i = 1: num_of_indicators

  Do Compute the Aggregated Distance (AD_i)
     between every indicator and rest

while size_of_set > desired_size_of_set

  Do Select  a pair of indicators so that
     Pair =  min{D_ij}

  Do Eliminate an indicator (I) from the
     pair so that I = min{AD_i}
```

Figure 5.2: Index selection procedure pseudo-code.

5.4 Optimisation Method

Transmission expansion planners need to assess the influence of their potential actions in different aspects of power systems’ operation. Technical and economic issues, as well as environmental impacts, have to be considered in the decision process. This leads to competing criteria, which are generally non-commensurable and whose relative influence is usually not definable. In such a situation, non-dominated optimisation becomes useful. This technique identifies a set of feasible non-dominated trade-off solutions, meaning that they are equal-rank optimal [160].

A multi-objective optimisation problem may be stated so that:

$$maximise \quad F(x) = (f_1(x), ..., f_m(x)); \quad Subject\ to \quad x \in \Omega \tag{5.13}$$

Where f_i $(i = 1, m)$ is the set of m objective functions in terms of the decision variable x, within the decision space Ω.

Let us assume two vectors so that $u = (u_1, ...u_m), v = (v_1, ...v_m) \in R^m$, being R^m the 'objective space'. u is said to dominate v if $u_i \geq v_i$ for every $i = 1, ...m$ and $u \geq v$. According to Pareto optimality, a solution $x^* \in \Omega$ is said to be optimal if there is no $x \in \Omega$ so that $F(x)$ dominates $F(x^*)$. In other words, a solution is said to be Pareto-optimal if none of the objectives can be improved without worsening another [161].

Instead of providing a unique (quasi) optimal solution, Pareto optimisation provides a set of trade-off solutions amongst which decision makers may choose depending on their needs [161]. Therefore, Pareto optimisation brings useful information about different decision objectives. Transmission expansion planning entails long term development projects, which are affected by several operating, administrative and legal issues. To cope with eventualities, it is useful to have a handful of alternatives. Nonetheless, the number of Pareto-optimal solutions may be large, so it is necessary to select the best compromise solution among them [160].

Several techniques to reduce the Pareto set have been proposed, some of them based on user preferences, clustering or distance. A review of common methods for Pareto set reduction can be found in [162]. User preference methods require a predefined preference, usually related to the weights of the objectives, to select a reduced set of solutions. Clustering methods reduce the Pareto set by dividing it into a predefined number of clusters and selecting those solutions that are closer to the centroid of each cluster. Finally, distance-based methods reduce the Pareto front by selecting those solutions that are closer to a reference or ideal point [162].

Notwithstanding, the specific characteristics of transmission expansion planning make these methods less suitable for FACTS devices' placement problem solving. User preference methods are conditioned by the pre-defined preferences and their results are only optimal for that particular case. On the other hand, clustering methods are not designed to provide a unique solution. Finally, the distinct nature of the variables that rule transmission expansion planning make it difficult to set appropriate reference or ideal points for distance-based methods. Furthermore, these techniques are intended for very large Pareto sets, and thus they are less suitable for the relatively small sets of solutions that are common in transmission expansion planning.

Taking this into account, a FACTS devices' placement method, based on Pareto optimality, and an alternative Pareto set reduction method are proposed here. Using the proposed indices selection method, two indices are selected from the set of predefined ones. Then, Pareto optimality is used to select the optimal solution(s). If more than one Pareto-optimal solution is provided, a third index will be selected and the trade-off solutions will be ranked according to this new index. The overall optimal solution will be the Pareto-optimal solution that maximises the mean relative improvement (MRI) of the third index so that:

$$Maximise \quad MRI_j^i; \quad Subject\,to \quad i \in \iota \tag{5.14}$$

Where j denotes the index to which the MRI is referred and i denotes the location of the device within the set of ι Pareto-optimal solutions.

Chapter 6

Experimental Work

In this research, three experiments have been carried out to provide interesting insights to the topic. Specific tests have been executed for a deeper analysis of the problem. This chapter is aimed at describing the experimental work performed to test the formulated hypotheses. Subsequently, the power system simulator, as well as the FACTS device model, used in the experiments are described. A description of the experiments, their methodology and the input data is also included. Finally, the obtained results are provided and discussed.

6.1 Simulator

In this section, a description of the power system simulator used in the experiments is provided. This simulator is formed by a grid simulator, based on the IEEE 14-bus test system, and a FACTS device model. A particular type of FACTS device, the static synchronous compensator (STATCOM) has been chosen given that it has been commonly used due to its satisfactory performance.

6.1.1 IEEE 14-Bus Test System

In order to test our proposal, we chose a specific type of FACTS device to be placed in a benchmark power system. The simulations were performed using PSS-E® 34 [163].

The IEEE 14-bus test system (Figure 6.1) represents a portion of the american electric power system as of February, 1962 [164]. It is composed of 20 branches, 14 buses, two generators (buses 1 and 2), three synchronous condensers (buses 3, 6 and 8), a capacitive switched shunt (bus 9) and 11 loads. The sum of the loads of this benchmark system is 259 MW and 77.4 MVAr.

The switched shunt in bus 9 has been removed from the system during the calculations so as to make our results comparable with those in [101] and other papers.

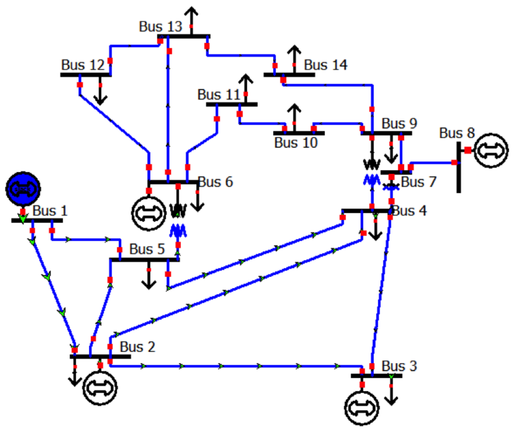

Figure 6.1: IEEE 14-bus test system.

6.1.2 FACTS Device Model

The STATCOM is a particular type of VSC which is intended to dynamically generate or absorb reactive power in a fast and robust way [19]. These devices are often connected to a step-up transformer and can be modelled either as a variable voltage source or a synchronous condenser for steady-state studies (Figure 6.2).

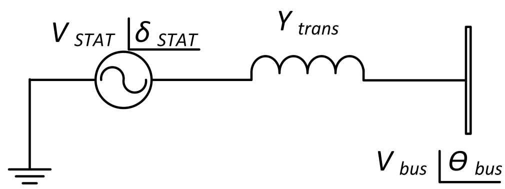

Figure 6.2: Schematic representation of a STATCOM model.

In this study, the STATCOM has been simulated as a synchronous condenser, which provides full voltage control within its maximum and minimum rated power. In order to do so, the specific tools for FACTS devices modelling provided by PSS-E [163] has been used.

6.2 Experiments

This section is intended to describe the different experiments carried out in this research. An experiment has been performed to evaluate the influence of load share on the FACTS devices placement problem. Furthermore, an experiment intended to test the first hypothesis and the proposed method for FACTS devices placement, attending to load share, is also presented. Finally, an experiment aimed to validate the hypotheses related to voltage control using FACTS device is included. The sensitivity of this analysis to load variations is also addressed.

6.2.1 Effect of Load Share on FACTS Devices Placement

As theoretically proven in chapter 4, load share conditions the result of FACTS devices placement. However, an empirical demonstration is needed to validate this conclusion. Furthermore, it is interesting to understand how load share influences the result of the FACTS devices placement. With this aim, we have performed an experiment that includes all suitable load share combinations for a fixed value of aggregated load. A detailed description of this experiment is presented below. It is important to mention that this experiment was published as a research article in an indexed scientific journal [165].

In order to facilitate the understanding of the results, we must provide further information about this research. First, we must point out that the available locations in which the STATCOM can be set are buses 4, 5, 9, 10, 11, 12, 13 and 14. Secondly, we must define the three demand zones, which are formed by buses 2 and 3 (demand zone 1), buses 4, 9, 10, 11 and 14 (demand zone 2), and buses 5, 6, 12 and 13 (demand zone 3) (Figure 6.1). Transformers between buses 5 and 6 and between buses 4 and 9 serve as boundary of demand zone 1. Demand zones 2 and 3 comprise buses one and two buses away from transformers 4-9 and 5-6 respectively.

Load Share Scenarios

Firstly, the nodes within the power system are split into three demand zones (Figure 6.1). By doing so, every load scenario can be identified by its three-dimensional coordinates, referred to as its load share. Using the representation procedure developed in [166], the three-dimensional load share data can be represented in a two-dimensional space. Demand zones are predefined according to the topology of the grid.

Later on, several load share scenarios are iteratively created by distributing the total system load among the three demand zones. In each iteration, the share of the system load assigned to every demand zone changes by a fixed step, which is defined as a percentage of system load (5%). Total system load is iteratively distributed between the different demand zones attending to the restriction in Equation (6.1) (Figure 6.3).

$$P_{sys} = P_{zone1} + P_{zone2} + P_{zone3} \quad (MVA) \tag{6.1}$$

where P_{zone1}, P_{zone2} and P_{zone3} represent the load in every demand zone and P_{sys} is the total system load.

The load assigned to every demand zone is distributed among the corresponding nodes respecting its original share.

Simulation Procedure

Once a load scenario is created, the FACTS placement procedure is initiated. In the first step, a P-V analysis is performed to evaluate the voltage stability of the current system configuration without FACTS device. Thereafter, for each of the predefined available locations, the device is set and configured at the corresponding node, and the P-V analysis is then reinitialised. This procedure is repeated for each load share scenario, respecting Equation (6.1) (see figure 6.3).

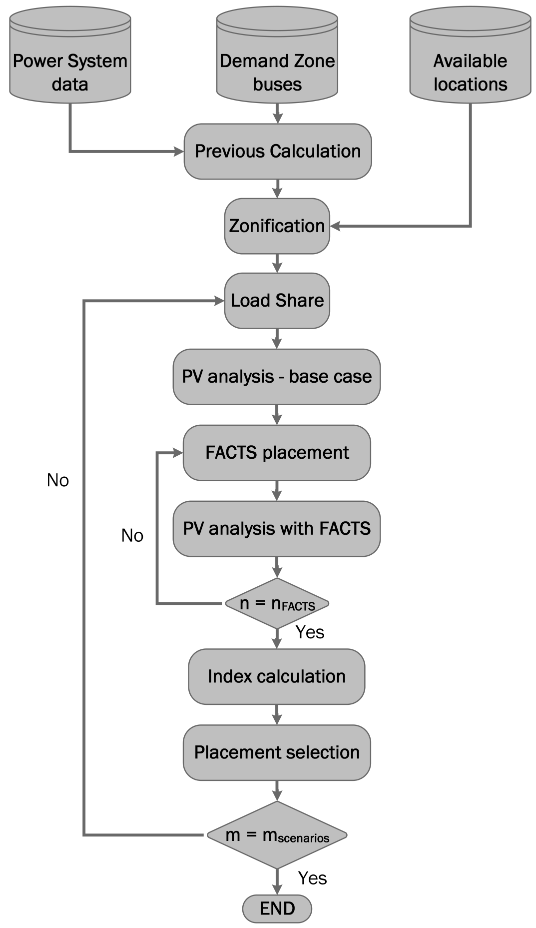

Figure 6.3: Simulation process flow chart.

The STATCOM model has been configured as follows: S_{max} = 100 MVA and $V_{ref} = V_{bus}(p.u.)$. Where V_{bus} is the voltage at the bus in which the device is installed at the base case.

Optimisation

From the results of every P-V analysis, a fused performance index (FPI) is calculated. The objective of the optimisation procedure is to maximise loading margin (6.2) and to minimise voltage deviation (6.3) and reactive power loss (6.4) using the worst-case criterion. This procedure is based on the one described in [101]. Nonetheless, changes have been made so as to take load share into account.

$$max\ \lambda = \lambda(v,u) \tag{6.2}$$

$$min\ VD = \sum_{bus=1}^{bus=n} \left| \frac{V_{rated} - V_{bus}}{V_{rated}} \right| \tag{6.3}$$

$$min\ QL = QL(v,u) \tag{6.4}$$

The optimal location for FACTS devices is then defined by the optimal (maximum) value of the fused performance index (FPI), which in turn is determined by the minimum value among the three optimisation functions stated in (6.5)–(6.7).

$$LMI_i = \frac{\lambda_i - \lambda_{min}}{\lambda_{max} - \lambda_{min}}, \quad for\, \lambda_{min} < \lambda_i < \lambda_{max} \tag{6.5}$$

$$VDI_i = \frac{VD_{max} - VD_i}{VD_{max} - VD_{min}}, \quad for\, VD_{min} < VD_i < VD_{max} \tag{6.6}$$

$$QLI_i = \frac{QL_{max} - QL_i}{QL_{max} - QL_{min}}, \quad for\, QL_{min} < QL_i < QL_{max} \tag{6.7}$$

In Equation (6.6), VD is the sum of the deviations of the voltage from its rated value (1 p.u.) at the nodes in which a violation of the voltage limits (0.95–1.05 p.u.) has occurred (Equation (6.3)).

The functions used here, except for LMI, refer to a single loading level within the P-V analysis. In order to enable comparison among the results for each FACTS device location, the indices must be calculated for the same loading level at every iteration within a load share scenario. Thus, we have determined this to be the maximum loading level handled by the system without FACTS device (base case).

We did not make any assumption about whether maximum or minimum values of λ, voltage deviation or reactive power loss correspond to the base case or not. This means that these values must be computed and that the base case is treated in the same way as the available locations. Therefore, it is possible for the optimal choice, at any load share scenario, to be the base case. In other words, it is possible that the best option may be to not install a FACTS device.

A multi-objective problem can be solved as a max-min optimisation problem, which implies a worst-case scenario approach [167]. This approach is particularly appropriate for power system planning studies due to the magnitude of investments as well as the criticality of electrical facilities.

In the context of the problem of this paper, the worst-case decision may be implemented as max-min optimisation problem that can be stated as:

$$WCD(v) = min\{OF_1(v), OF_2(v), ..., OF_n(v)\} \quad subject\ to: c_1(v), c_2(v), ..., c_m(v) \tag{6.8}$$

$$OS = \underset{v \in V}{argmax}\{WCD(v)\} \tag{6.9}$$

where $WCD(v)$ is the worst-case decision, $OF_1(v), OF_2(v), ..., OF_n(v)$ are the n objective functions, $c_1(v), c_2(v), ..., c_m(v)$ are the m constraints and V is the decision space.

Given that the whole space of load share has been sampled, relative frequency (f) can be used to determine which of the solutions performed better in a greater number of demand scenarios. Therefore, the multi-objective FACTS device placement problem can be stated so that:

$$FPI_{l,s} = min\{LMI_{l,s}(v), VDI_{l,s}(v), QLI_{l,s}(v)\} \quad subject\ to: g(v,u) = 0, h(v,u) \leq 0 \tag{6.10}$$

$$OL_s = \underset{l \in L}{argmax}\{FPI_{l,s}\} \tag{6.11}$$

$$MFOL = \underset{l \in L}{argmax}\{f_l\} \tag{6.12}$$

where l stands for every available location and L is the set of available locations. OL_s is the optimal location for a given load share scenario (s), $MFOL$ is the most frequent optimal location and f_l is the relative frequency of every l as optimal for different load share scenarios. On the other hand, g is the equality constraints of load flow equations and h is the set of system operating constraints so that:

$$V_{G_i}^{min} \leq V_{G_i} \leq V_{G_i}^{max}, \quad i = 1, ..., n \tag{6.13}$$

$$P_{G_i}^{min} \leq P_{G_i} \leq P_{G_i}^{max}, \quad i = 1, ..., n \tag{6.14}$$

$$Q_{G_i}^{min} \leq Q_{G_i} \leq Q_{G_i}^{max}, \quad i = 1, ..., n \tag{6.15}$$

$$Q_{C_i}^{min} \leq Q_{C_i} \leq Q_{C_i}^{max}, \quad i = 1, ..., m \tag{6.16}$$

where n is the number of generators and m is the number of FACTS devices.

Since the size of the device does not affect the effectiveness of the compensation, we can obviate this parameter within the allocation procedure. Moreover, this is a time-consuming task that can be carried out at a later time. Thus, we have considered the size of the FACTS device as a constant in this procedure.

In addition, in order to evaluate the performance of the FPI, we compared its results with those we obtained using λ as an objective function.

6.2.2 FACTS Devices Placement Using Distributed Data

Once the influence of load share on FACTS devices placement has been addressed, the procedure to optimally place FACTS devices using distributed data needs to be tested. With this aim, an experiment has been carried out so as to evaluate the performance of the proposed procedure. The influence of the amount and configuration of demand scenarios on FACTS device placement has been assessed. At the same time, this experiment provided useful insights on the sensibilities of the problem to changes in demand, particularly regarding to load share, but also to loading level.

Demand Scenarios

As mentioned in chapter 3, since light and temperature vary cyclically, with different periods, power demand also behaves cyclically in a particular manner. Furthermore, other power system agents behave following cyclic patterns. Photovoltaic plants are good examples of this kind of agents. Thus, we consider that the coincidences of the demand and generation patterns need to be taken into consideration when studying power systems.

Since power grids aggregate loads by areas, groups of devices and customers with specific load characteristics may be designated. As demonstrated in [124], demand from different areas may differ noticeably, so demand from different substations may be treated specifically when studying power systems.

So as to consider the coincidence of patterns from different variables and the spatial distribution of demand, historical disaggregated demand data from [125] has been used for this experiment. Data has been treated so that load data series with greater standard deviation were assigned to demand buses with smaller mean power. Additionally, each data series was treated so that its maximum annual power coincides with the power of the load bus to which it is assigned.

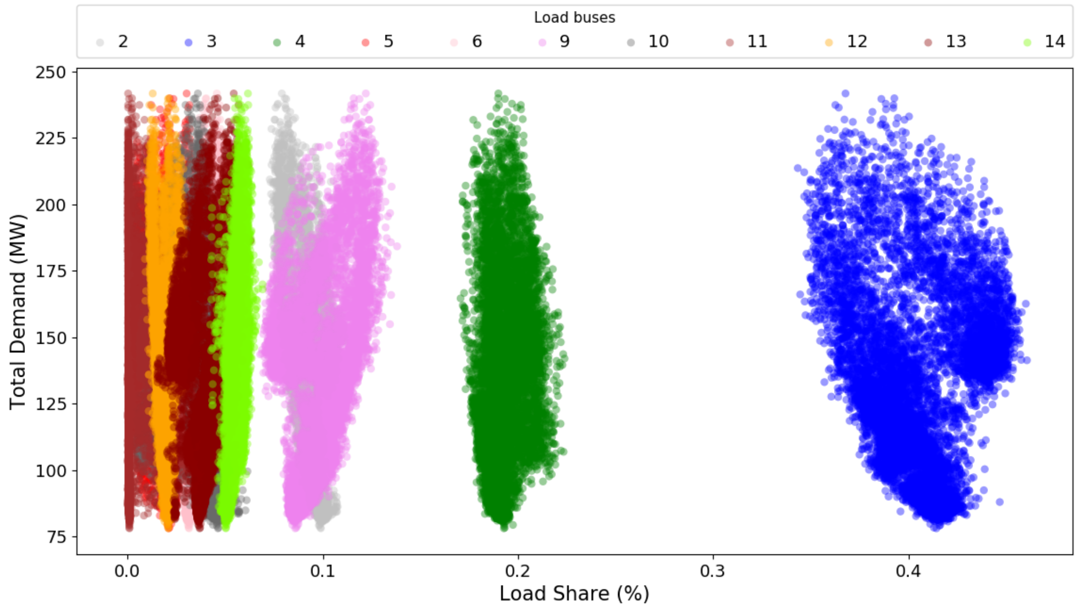

Figure 6.4: Demand scenarios as a function of total power and load share.

The geographically distributed demand data covers a period of one year with hourly demand scenarios. In figure 6.4, demand scenarios are represented in terms of their total power and the load share of all load buses. Thus, for every hour of the year, a set of n points is plotted in the chart, being n the number of load buses. The points corresponding to the same demand scenario share the same y coordinate, which represents the total amount of demanded power. The x coordinate represents the share of the total demand (for that particular scenario) that corresponds to every particular bus as a percentage, the load share.

In figure 6.5, a histogram of aggregated power is shown, so that its distribution density can be appreciated.

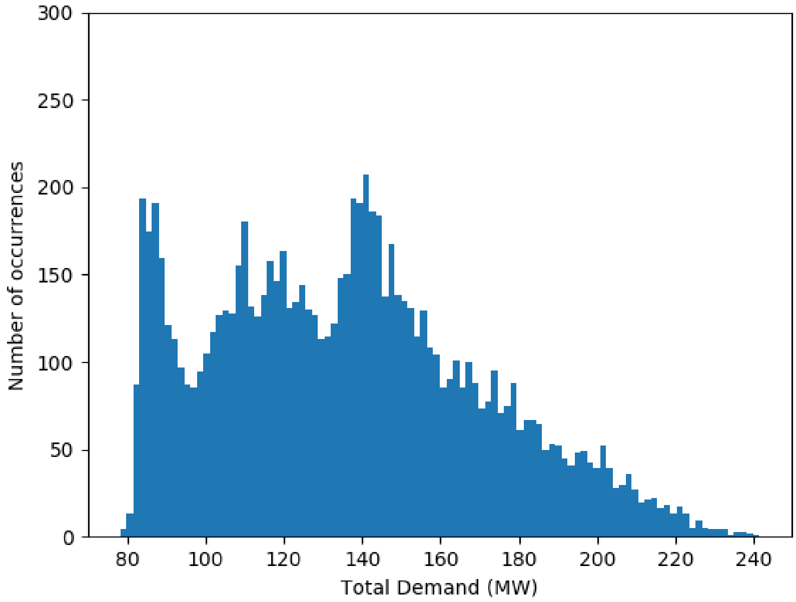

Figure 6.5: Demand scenarios histogram.

Methodology

This experiment is aimed to include a sufficient number of demand scenarios to adequately account for demand variations. As previously mentioned, in a context in which renewable generators provide unmanageable power, customers take on more active roles and new technologies provide more sophisticated control strategies, the interactions between demand and these new determinants needs to be considered. In this experiment, a year of hourly geographically disaggregated demand data is used as an input for FACTs devices placement. This approach is compared to the traditional peak and valley approach. The methodology of this experiment has been described in chapter 5. However, a brief resume will be provided here.

Based on a set of 8760 distributed demand scenarios, optimal power flow was used to configure each demand scenario prior to the analysis. P-V curves were created by iteratively performing power flow calculations with increasing load values. By doing so, several variables could be measured in different demand scenarios and with different loading levels. Voltage stability and thermal restrictions were used to ensure suitable calculations.

Different indices were computed using the collected data, namely: voltage deviation, active power losses, reactive power losses, loading margin, operating costs and greenhouse gases emissions. These indices measured the mean relative improvement of power system operation, and were used to compare the impact of the FACTS device in the different available locations. However, a reduced number of indices needed to be included in the FACTS devices placement procedure. Thus, a mutual information-based index selection method was used to find a reduce subset of indices with the most complementary information about the problem.

Finally, a decision-making algorithm based on Pareto optimality was used to search for the location(s) in which a greater enhancement of operative variables is found. The available locations in which the STATCOM can be set are buses 4, 5, 9, 10, 11, 12, 13 and 14.

6.2.3 FACTS Devices Control Configuration Using Distributed Data

Once an optimal location is found for a FACTS device, the next step is to optimally configure it for the best achievable performance. Several parameters need to be configured so as to optimize the response of the device to the likely operative situations. However, since this study is focused on steady-state analysis, the research will be directed to investigate the sensibilities of the reference value for voltage control. Therefore, this experiment is intended to determining the influence of the voltage control reference value and its sensibility to changes in demand. In particular, distributed demand data is used to assess the influence of loading level and load share on the result of the voltage control reference value selection.

Load Share Scenarios

In order to test the different solutions (reference values), respecting the representativeness of the base data and the cyclic coincidence of the involved variables, historical distributed data has been chosen for demand scenarios creation. A set of 8760 hourly scenarios has been created from data measured for a period of one year. Both the historical data and the procedure for scenarios generation are exactly the same as the experiment with "FACTS devices placement using distributed data". Therefore, the demand scenarios used in both experiments are exactly the same.

Methodology

Similarly, the methodology described in chapter 5 is used in this case to analyse the influence of load variation in the selection of a reference value for voltage control using FACTS devices. Nonetheless, in the case of this experiment, different reference values have been tested, while the bus in which the device is installed becomes a control variable. Anyhow, OPF is calculated for every demand scenario and a P-V study is performed. Based on the results obtained, indices are calculated and Pareto optimality is used to search for the best solutions. Voltage control reference values from 0.98 p.u. to 1.05 p.u., in steps of 0.01 p.u., have been tested. Additionally, different test have been carried out to show the sensitivities of this optimisation to changes in demand.

6.3 Results and Discussion

In this section, the results of the different experiments are presented. A brief introductory explanation of the representation procedure is included, particularly in the case of the experiment on the effect of load share on FACTS devices placement. In addition, a discussion about the implications of the results is provided.

6.3.1 Effect of Load Share on FACTS Devices Placement

The results obtained from the simulations comprised in the experiment on the effect of load share on FACTS devices' placement are presented first. It is worth noting that, in order to represent the results so they can be easily understood, we have used the representation procedure developed in [166]. The main characteristic of this procedure is that it enables us to represent three-dimensional data, the load share of the three demand zones, into a two-dimensional space, using the interdependence of the variables (Equation (6.1)).

The triangle in the following figures shows the best placement of the STATCOM for each load share scenario. Each corner of the triangle represents the load share scenario in which the total system load is set into only one of the demand zones. Thus, points inside the triangle represent the shift of the load from one demand zone to the others, respecting the restriction stated in (6.1). Consequently, the centroid of the triangle coincides with the situation in which the load assigned to each demand zone is the same ($1/\widehat{3}p.u.$ each). The presence of blank spaces in the chart corresponds with the existence of instable load share scenarios whose power flow could not be calculated.

Each point in the chart represents a solution to the placement procedure based on a load share scenario. At the same time, the colour of each one refers to the number of the selected bus. It is worth noting that there are no available positions in demand zone 1. Thus, we have grouped the colours that represent the selected nodes into two ranges: we represent nodes from demand zone 2 with blue and nodes from demand zone 3 with red. Furthermore, darker colours represent nodes furthest away from generation (placed in nodes 1, 2 and 3).

The most remarkable conclusion to emerge from the data analysis is that the result of the FACTS placement procedure often changes, depending on the load share scenario. Nevertheless, contrary to our expectations, we found that the solution drastically changed from one load share scenario to the other (Figure 6.6). For this reason, we filtered the results of the sub-indices (λ, voltage deviation and reactive power loss) using a simple mean filter [168] in order to smooth the variation of the FPI (Figure 6.8). At the same time, the values of λ have also been filtered when it is used as an objective function.

Regarding the filtered results, we should mention that there are substantial discrepancies between the results of FPI and λ as objective functions. The optimal location for a given load share scenario does not coincide for both indices in most cases, nor does the frequency of the solutions (Figure 6.7).

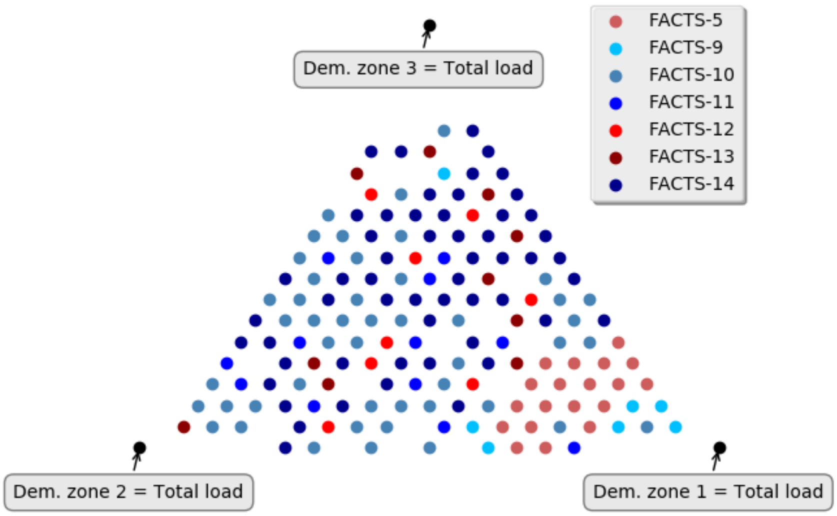

Figure 6.6: Best FACTS locations according to FPI and demand scenarios.

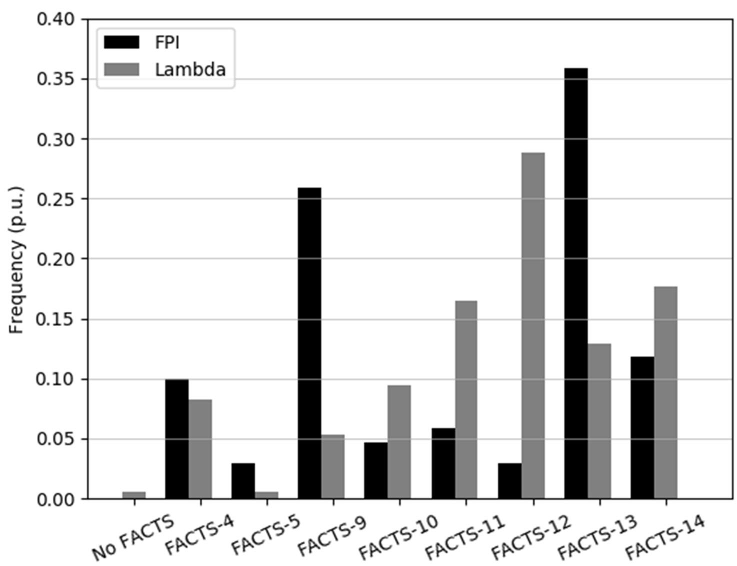

Figure 6.7: Frequency of the filtered solutions depending on the objective function.

Using the FPI as the objective function, the most frequently selected locations were buses 5 and 13, which were chosen in more than 60% of the load share scenarios. In contrast, using λ as the objective function, the most frequent choice was, undoubtedly, bus number 12, which comprises around a third of total solutions. Given these discrepancies, results from both objective functions must be analysed separately. In Table 6.1, these results can be compared with those from similar approaches in the literature that, in contrast, do not take load share into account.

It is worth noting that, together with the number of the selected bus, this procedure provides a performance index: FPI or λ. These two parameters provide different information for decision making. Therefore, the following comparative analysis was carried out on the basis of a graphical marriage between selected bus number and index value attending to the different load share scenarios.

Paper	FACTS Type	OF	OL
Present	STATCOM	λ	12
Present	STATCOM	FPI	13
[101]	STATCOM	FPI	9
[21]	STATCOM	Ev, VD, Size	9

Table 6.1: FACTS devices placement results. Comparison between different objective functions.

FPI as Objective Function

Analysing the FPI as an optimisation function more deeply, we obtained the following results. In regards to which demand zone the nodes belong to, nodes from demand zone 2 (blue colours) were more frequently selected when zones 1 and 2 were overloaded (see figure 6.8). More precisely, whenever demand zone 1 becomes more and more loaded, the preferred options become bus number 4 and 5, which are directly linked to the area. This may be due to the fact that there is no available location in demand zone 1. On the other hand, bus number 9 was preferred when demand zone 2 was the most loaded one.

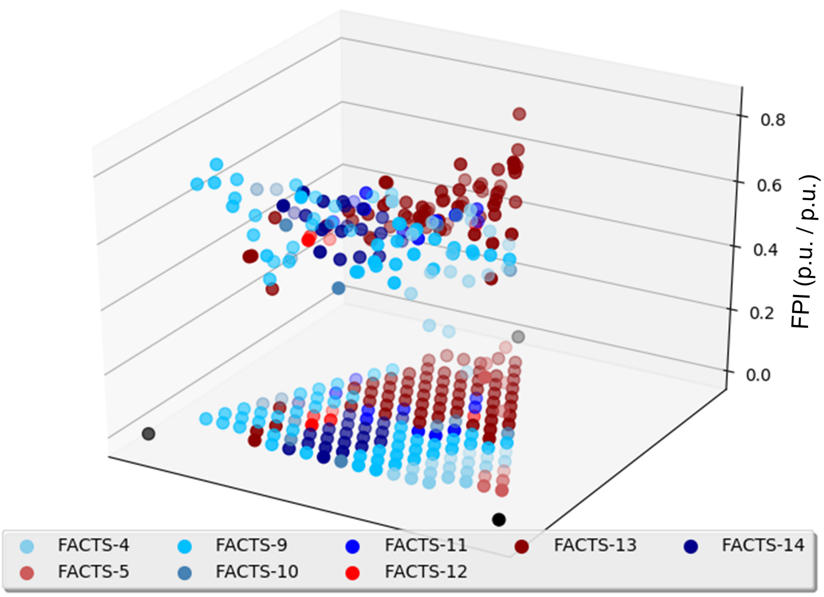

Figure 6.8: Best FACTS locations and FPI values according to demand scenarios.

When load shifts to demand zone 3, solutions from the same area (red colours) predominate. In particular, bus number 13 proved to be the most frequent solution in this situation.

Additionally, further analysis has shown that the values of the FPI tended to be dispersed. Focusing on this tendency, we found that their value increased when load shifted to demand zones 2 and 3, while they strongly decreased when load tended to concentrate in demand zone 1.

Lambda as Objective Function

In a similar manner, when using λ as an optimization function, the tests revealed that solutions from demand zone 2 clearly predominated as demand zones 1 and 2 were the most loaded ones (see figure 6.9). Nevertheless, in this case, bus number 14 proved to be the most suitable solution when demand zone 2 was overloaded, while bus number 4 proved to be the best choice when load shifted to demand zone 1. Finally, buses from demand zone 3, especially bus number 12, were preferred when load moved to that area.

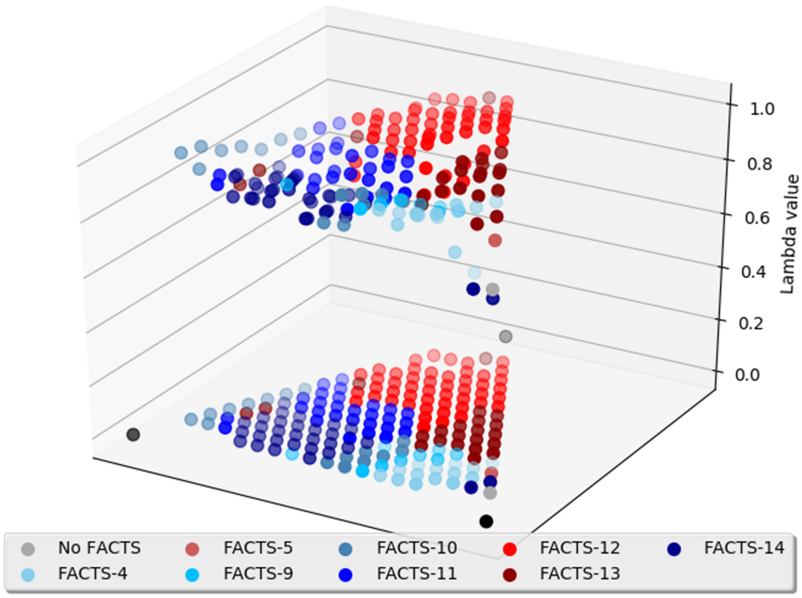

Figure 6.9: Best FACTS locations and λ values according to demand scenarios.

From a quantitative point of view, the simulations have shown that the values of λ tended to remain more concentrated than those of the FPI. Nevertheless, they tended to rise when load shifted to demand zone 3. On the other hand, they fell drastically when load approached demand zone 1.

Although there were some discrepancies between results using different objective functions, we believe our results to be consistent with the expectations.

To begin with, our findings appear to be well supported by previous studies that demonstrate that buses from 9 to 14 are the weakest within the grid ([101, 41]). Nevertheless, the weakest bus is not always the best choice for compensation [101]. Moreover, since the effectiveness of voltage regulation is mainly local, it is expected, for FACTS optimal location, to be near the weakest buses. The results show that the most frequent locations were bus 13 for FPI and bus 12 for λ, which surround bus 14 and are close to bus 9.

Secondly, as we have theoretically proven, load has a major impact on FACTS placement selection. In short, the critical buses in terms of voltage collapse may differ from one demand scenario to the next, since bus load strongly influences bus voltage. Therefore, FACTS optimal placement is expected to approach to the most loaded areas.

Remarkably, the results we obtained seem to follow this double correlation. On the one hand, the most selected buses coincide with the weakest ones. On the other hand, the selected bus tended to be within, or in the vicinity of, the most loaded demand zone.

Apart from that, even though their behaviour differs, both indices captured the effect of the absence of available locations in demand zone 1. While λ tended to remain more stable, the FPI tended to fluctuate, augmenting when load concentrated in demand zones 2 and 3. Nevertheless, when load shifted to demand zone 1, both indices' values sank.

In addition, despite there being no good agreement between results using different objective functions at a bus level, there is at a demand zone level. Buses from demand zone 2 proved to be preferred when load shifted to demand zones 1 and 2, while buses from demand zone 3 performed better when their zone was overloaded. Taken together, these results would seem to suggest that both λ and FPI work well for FACTS devices placement. Nevertheless, they have different meanings. On the one hand, λ indicates how much load can grow in a safe manner, so it is suitable for mid and long term planning. On the other hand, FPI also takes into account operation variables, such as voltage and reactive power loss. Which one should be used by decision makers depends on the scope of the study being performed.

6.3.2 FACTS Devices Placement Using Distributed Data

In this section, the results obtained from the implementation of the proposed methodology for FACTS devices placement are shown. This experiment is intended to demonstrate that, taking into account a greater number of demand scenarios, more robust results may be obtained. As previously argued, not only the variations of the amount of demanded power, but also the variations of load share, may influence the solution of the FACTS placement problem.

Index Selection Results

First, the results of the index selection method are presented. This method is based on a metric of the distance between indices in terms of their shared information, the $D-distance$. Using the information theory, those indices providing the most complementary information may be used for FACTS devices placement. Therefore, indices with greater distance are selected as the ones which provide more heterogeneous information. As described in section 2.3, prior to the calculation of D, the indices have been filtered so as to exclude those with irrelevant influence on the problem. We have considered those indices with a mean relative improvement (MRI) so that $\overline{MRI} \leq 0.005$ and $\sigma_{MRI} \leq 0.025$ have an irrelevant influence on the problem. As a result, operation costs and greenhouse gases emissions have been excluded from the analysis. In table 6.2, the value of the $D-distances$ for every relevant combination of indices is shown.

As can be seen, the loading margin presents a large distance with respect to the rest of indices, meaning that it shares little information, and thus it is complementary, with them. In contrast, voltage deviation, reactive power losses and active power losses show a smaller distance, meaning that they share a relatively larger amount of information. This is particularly true for active and reactive power losses.

	λ	**Volt. Dev.**	**Q Loss**	**P Loss**
λ	0	0.8323	0.8436	0.8496
Volt. Dev.	-	0	0.6787	0.7295
Q Loss	-	-	0	0.3478
P Loss	-	-	-	0

Table 6.2: D-distance between all relevant indices belonging to the original set.

It is important to note that, in combination with the MRI indices, the $D-distance$ measures to what extent two indices provide the same information about the behaviour of the power system as a consequence of the presence of the FACTS device. A comparative analysis may be performed for the different locations since the same simulating conditions have been used. Given that the indices are calculated as the relative improvement of system variables due to the FACTS device, the effect of demand scenarios is eliminated. Thus, the results must be interpreted from this perspective.

Firstly, the loading margin (λ) shows the greatest distances with respect to the rest of indices. This may be due to the fact that λ measures the distance between the actual amount of aggregated power and the critical loading level for a particular demand scenario. In contrast, the remaining indices are related exclusively to the actual loading level. The impact of the FACTS device may be completely different near the normal operative conditions than in extreme conditions, due to the nonlinear behaviour of power systems' variables. This may justify the dissimilarities between λ and the rest of indices.

On the contrary, voltage deviation, reactive power losses and active power losses show smaller values of $D-distance$, particularly between active and reactive losses. It is reasonable to think that reactive power loss acts as a nexus between voltage deviation and active power losses. Certainly, reactive power has a direct and major impact on bus voltages, which in the end conditions line flows. When analysing the influence of reactive power losses on bus voltages and active power loss it is important to consider that the main variations in this study are related to the reactive power provided or absorbed by the FACTS device. The reactive power output varies as a consequence of the changes in demand, which are the same for all the locations studied. Hence, the information included in the reactive power loss index may be supposed as implicitly and partially present in the indices referred to voltage deviation and active power loss. However, both of them have their own determinants; voltage is highly influenced by generation and load distribution, as well as the impedance of the transmission paths, and active power losses are function of the real part of the impedance of the transmission paths and the lines' current. Consequently, although they may share a certain amount of information, there always will be a certain degree of complementarity between them.

As a result of the index selection method, loading margin and voltage deviation have been selected as the most complementary subset of indices. This is consistent with some findings of the literature review, which showed that voltage stability indices were preferred by researches for FACTS devices placement [9]. These indices were followed by active and reactive power losses and devices' cost. Therefore, loading margin and voltage deviation have been used as a measure of the FACTS device's impact on the benchmark power system.

FACTS Devices Placement Results

In this section, the FACTS devices placement problem is analysed in terms of loading margin and voltage deviation. At the same time, the experiment is used to test the proposed methodology. With this aim, mean and standard deviation for every index are calculated on the basis of the values obtained from the 8760 hourly demand scenarios. In figures 6.10 and 6.11, mean and standard deviation of voltage deviation and loading margin relative improvements, respectively, can be found for all candidate solutions. It is worth recalling that candidate solutions for FACTS devices placement are buses 4, 5, 9, 10, 11, 12, 13 and 14.

As mentioned in chapter 5, all indices have been designed so as to enable their maximisation using Pareto optimality. They are relative measures of the difference between system variables with and without compensation, so positive values should be considered an improvement of the variable to which the index is referred, and *vice versa*. Consequently, from here on, the results are referred to as loading margin increase and voltage deviation decrease.

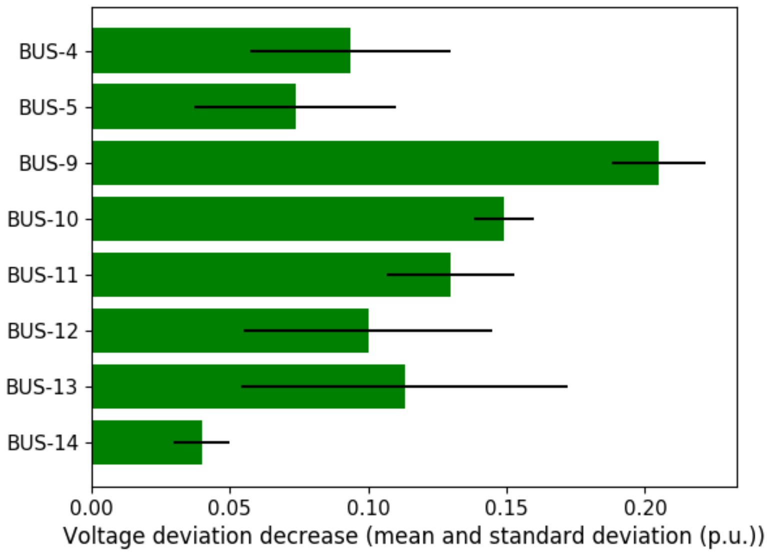

Figure 6.10: FACTS devices placement. Mean and standard deviation of voltage deviation decrease.

Similarities between the relative "goodness" of the different locations in terms of voltage deviation decrease and loading margin increase may be found. However, a substantial difference needs to be highlighted. While, for voltage deviation decrease, bus 9 is doubtlessly the best location, and bus 14 is the worst at a distance; in terms of loading margin increase, bus 14 becomes the second best option with little difference from bus 9.

Bus 14 has repeatedly proved to be the critical bus in terms of voltage stability ([96] and [41]). However, bus number 9 has been selected as the preferred location for FACTS devices

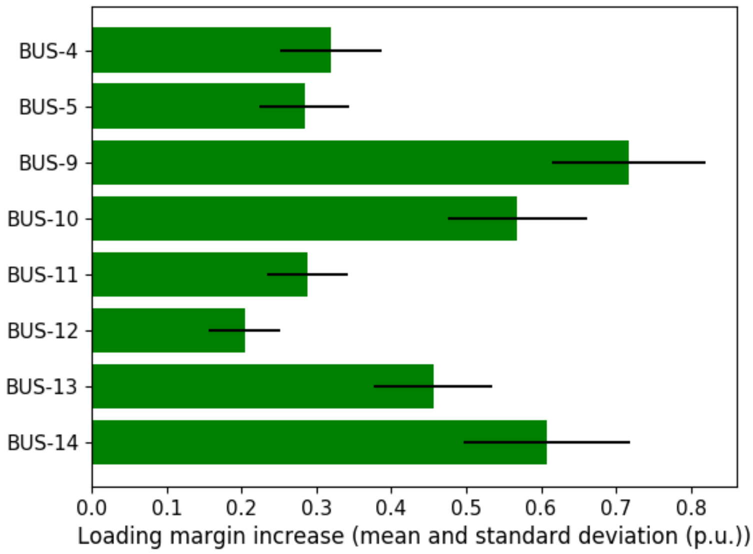

Figure 6.11: FACTS devices placement. Mean and standard deviation of loading margin increase.

in different studies ([101] and [21]). The great influence of bus number 9 on the voltage of its surrounding buses may justify its good performance in both indices. On the contrary, bus 14 does not present a noticeable influence on voltage profile. Nonetheless, as long as it is the critical bus, it highly influences system-wide loading margin.

Based on the results of the indices selection, the proposed procedure was implemented. Thus, voltage deviation decrease and loading margin increase were chosen for FACTS devices placement based on Pareto optimality. In figure 6.12, voltage deviation reduction and loading margin increase values are plotted for every available location. Solutions which comply with Pareto optimality are plotted in green, while those that worsen some of the objectives are plotted in red.

The results show that none of the available locations present a negative average impact in power system operation, so all of them would lead to an enhancement of both operative variables. Nonetheless, a remarkable variation the indices' values is found. Voltage deviation decrease ranges from less than $0.05 p.u.$ to more than $0.2 p.u.$, while loading margin increase ranges from $0.2 p.u.$ to more than $0.7 p.u.$. However, solutions may be categorized in three different groups. Firstly, buses 4, 5, 11 and 12 show relatively small improvement of both indices. Secondly, bus 14 shows good performance in terms of loading margin, but it is the worst solution in terms of voltage deviation. Finally, buses 9, 10 and 13 present good results both in terms of loading margin and voltage deviation. However, the preferred solution is bus number 9, which is the only Pareto-optimal solution at a distance from the rest. This is consistent with previous studies, which showed that, when FACTS devices placement is based on the search for the best location for compensation, instead of searching for the weakest bus, bus 9 is preferred ([101] and [21]).

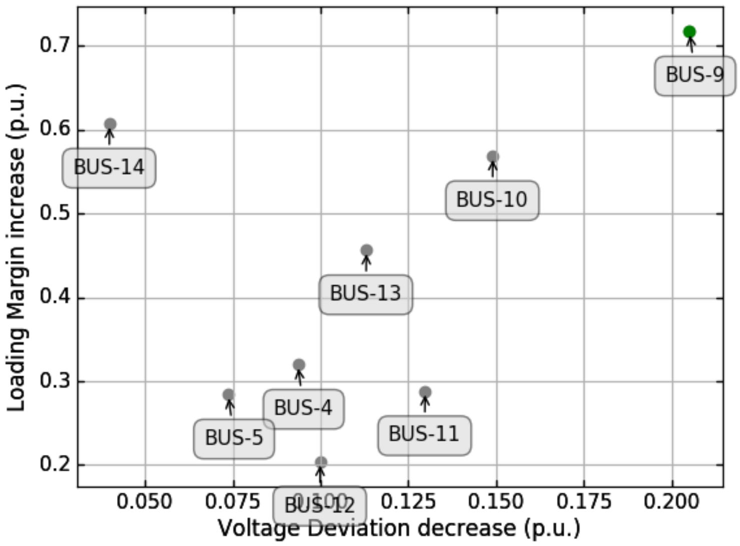

Figure 6.12: FACTS devices placement. Voltage deviation decrease versus λ increase according to demand scenarios.

Influence of Load Share on FACTS Devices Placement

As mentioned earlier, one of the objectives of this work is to investigate how load share influences FACTS devices placement procedures and their solutions. In order to analyse these interactions, a study on the variations of the indices' values as a function of load share ”flatness” has been carried out. With this aim, an index is used to measure this attribute of the demand scenarios. The flatness of the load share profile of a given demand scenario is defined as the ratio between the load percentage of the less loaded bus and the load percentage of the most loaded one. Therefore, it is computed as follows:

$$Fl = \frac{\min\limits_{1 \leq i \leq n} Lp_i}{\max\limits_{1 \leq i \leq n} Lp_i} \tag{6.17}$$

Where n is the number of load buses and Lp_i is the load percentage of the ith load bus for the given demand scenario (s), which is $Lp_i = P_i^s / Pt^s$. With P_i^s the active power of the ith bus in the s scenario and Pt^s the total aggregated power of the s scenario.

Taking the value of the flatness of all the demand scenarios, quartiles were calculated so as to separate the scenarios into four subsets. Then, the FACTS devices placement procedure was executed for each quarter of scenarios. Consequently, the performance of every available location has been evaluated for four different kinds of demand scenarios, from highly equally distributed demand scenarios (Q1) to highly unequally distributed ones (Q4). The results of this study are presented in figure 6.13.

Noticeable differences are found between results of the different quarters, up to the point that, analysing each index separately, the relative position of some solutions (locations) changes.

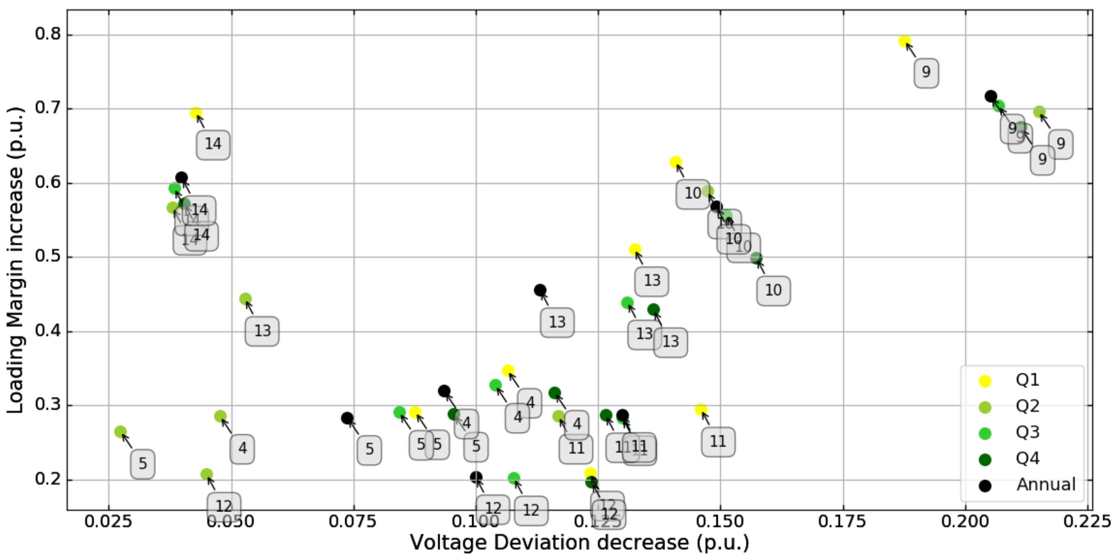

Figure 6.13: FACTS devices placement. Voltage deviation decrease versus λ increase as a function of load share flatness. Comparison with mean annual values. Scenarios with variable load share.

In addition, the influence of load share flatness changes depending on the location being studied. On the one hand, different tendencies are found in different locations in regard to the influence of load share flatness on both indices. For instance, for bus 14, the influence of load share is mainly proportional to loading margin increase, while, for bus 5, it seems to be proportional to voltage deviation decrease. On the other hand, a clear distinction is found between solutions that are highly sensitive to load share flatness and those that are not. Buses 4, 5, 12 and 13 show very dissimilar results depending on the quarters, especially in terms of voltage deviation. In particular, Q2 scenarios provide a significantly reduced score in voltage deviation decrease at these buses. In contrast, buses 9, 10, 11 and 14 show little sensitivity to load share flatness. The approximate variation of these solutions as a function of load share flatness is $0.005 p.u.$ for voltage deviation decrease and $0.15 p.u.$ for loading margin increase. For the sake of comparison, the approximate variation of bus number 13, for voltage deviation decrease is 0.15, three times greater. This means that, for bus 13, depending on the load share flatness of the demand scenario, the improvement on voltage deviation due to the FACTS device may range from 5% to 13%. Mean annual values show a smoother behaviour, remaining in a central position with respect to the values obtained from stratified scenarios.

In terms of decision-making, bus 9 proved to be the optimal solution independently of the demand scenarios. Therefore, it may be concluded that, although voltage deviation decrease and loading margin increase are sensitive to load share flatness, the placement decision is robust.

Given the influence of load share on the results of FACTS devices placement, a comparative analysis was performed between the results obtained from demand scenarios with variable and constant load share. A set of demand scenarios with variable load share was created with historical data from [125], as described in chapter 5. Alternatively, based on this data, equivalent demand scenarios with constant load share were generated. To this end, total power was calculated for all demand scenario as the sum of the loads' active power. Then, these values were scaled so that the maximum aggregated load (peak scenario's load) is equal to the aggregated load of the IEEE 14-bus test system. Finally, for each demand scenario, the scaled aggregated load was distributed between the system's load buses using their original load share. For the rest of this experiment, results obtained from demand scenarios with variable and constant load share are compared.

Influence of the Demand Scenarios' Total Power on FACTS Devices Placement

A traditional approach used for power system studies and transmission system expansion planning is the peak/valley approach. In order to investigate the influence of the total power of the demand scenarios in FACTS devices placement results, a particular test was carried out. Similarly to the previous test, quartiles were calculated based on the total load of every demand scenario. Thus, quarters were created comprising demand scenarios of similar total power, from scarcely loaded demand scenarios (Q1) to highly loaded ones (Q4). The results of this test, for variable and constant load share scenarios, are presented in figures 6.14 and 6.15 respectively.

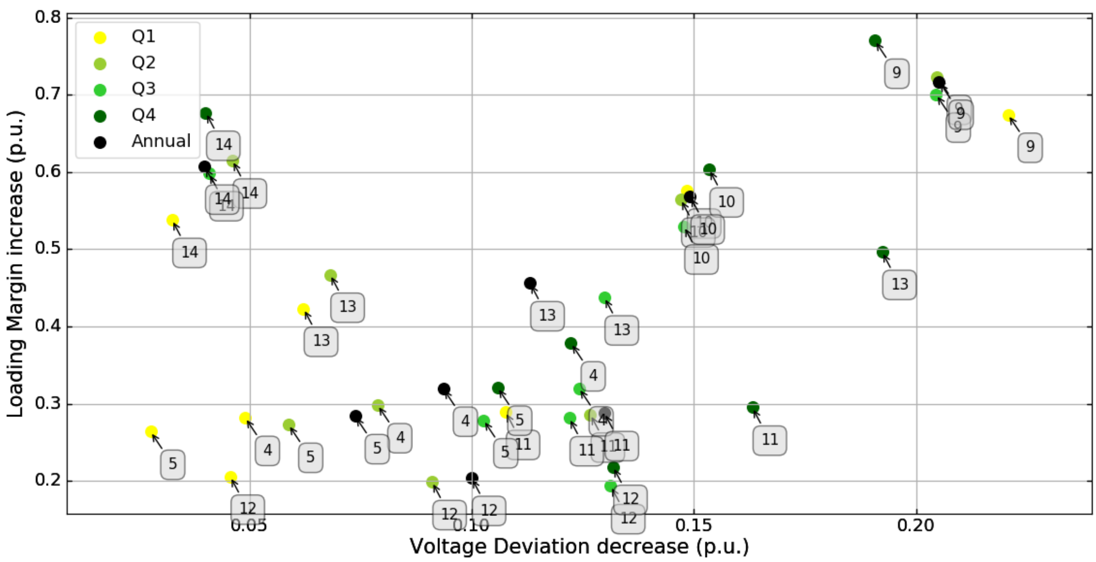

Figure 6.14: FACTS devices placement. Voltage deviation decrease versus λ increase for demand scenarios as a function of their total power. Comparison with mean annual values. Scenarios with variable load share.

Similarly to the results obtained from the different load share quarters' scenarios, the results of different total power quarters vary. On the one hand, like before, buses 4, 5, 11 and 12 present relatively worse results for both indices, while bus 14 stands out only in terms of loading margin increase. Contrarily, buses 9, 10 and 13 show good performance in regard to both indices. On the other hand, significant differences are found in terms of the sensitivity of the different solutions to the scenarios' total power. While buses 9, 10 and 14 show little sensitivity, buses 4, 5, 11, 12 and 13 are highly sensitive, particularly regarding voltage deviation decrease. It is worth pointing out the case of bus 13, which is the best option in terms of voltage deviation decrease for Q4, but it turns out to be the third worst for Q2, with approximate values of $0.19 p.u.$ and $0.07 p.u.$ respectively. On the contrary, voltage deviation decrease for bus number 9 ranges from $0.19 p.u.$ to $0.23 p.u.$. Loading margin results seem to be relatively less affected by the scenarios' total power, with variations around $0.1 p.u.$. Comparing the quarter-based results to the annual mean values, one can observe that the later tend to remain in a central position with respect to the first.

Once more, the preferred solution is bus number 9 in all cases. However, a remarkable difference from the previous results is found. In this case, results from Q4 scenarios show that bus 9 is preferred over bus 13 due to the small difference between them in terms of voltage deviation decrease. Nonetheless, in an strict sense, both are Pareto-optimal. Consequently, it may be argued that the decision on the FACTS device's location is sensitive to the demand scenarios' total power.

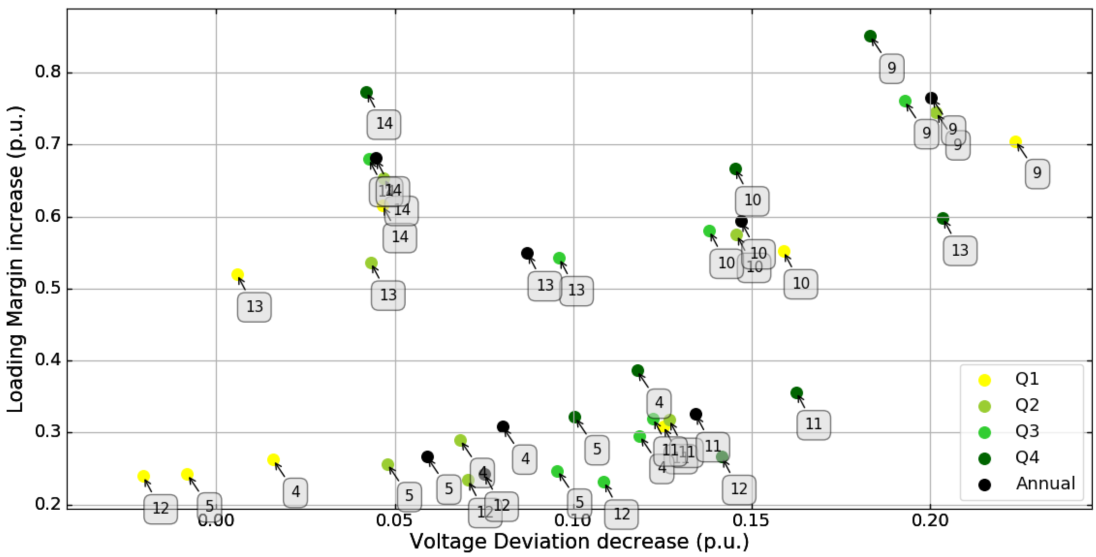

Figure 6.15: FACTS devices placement. Voltage deviation decrease versus λ increase for demand scenarios as a function of their total power. Comparison with mean annual values. Scenarios with constant load share.

Some differences may be found between results coming from demand scenarios with variable load share (figure 6.14) and those coming from demand scenarios with constant load share (figure 6.15). In the case of constant load share, results from different quarters provide more distant values for the same location. The values of loading margin increase tend to be higher, particularly for buses 9, 10, 13 and 14. The results show a greater sensitivity to the scenarios' total power as well. On the one hand, voltage deviation decrease ranges from $0.01p.u$ to $0.21p.u.$ for bus 13, while variations for buses 9, 10 and 14 remain within $0.06p.u.$. Finally, the sensitivity of the decision about the scenarios' total power becomes more evident, since it is clear that the Pareto-optimal solutions for Q4 are buses 9 and 13. It is worth mentioning that negative values of voltage deviation decrease appear for Q1 results in some locations, meaning that adverse consequences may derive from the FACTS device's operation.

To summarize, the results of the FACTS placement procedure are found to be sensitive to variations in demand scenarios' total power. Nonetheless, these sensitivities differ from one particular solution to another, and are also affected by the way in which load scenarios are created. Results from demand scenarios with variable load share are slightly different from those of constant load share. In terms of decision making, it is found that the shape and composition of the Pareto front may differ for highly loaded demand scenarios.

Comparison Between Mean Annual and Peak/Valley Approach on FACTS Devices Placement

The mean annual results have been compared to the results obtained from peak and valley scenarios. Nonetheless, as demonstrated in [26], peak demand scenario may not be the appropriate scenario for FACTS devices placement. For this reason, a test was performed to validate peak and valley scenarios as the worst and best scenarios in terms of voltage collapse proximity. First, maximum and minimum load scenarios were searched. Then, taking the annual results of the test power system without the FACTS device, maximum and minimum loading margin scenarios were searched as well. In order to determine if the peak scenario may be used as the worst-case scenarios, results of the peak/valley approach were compared to those of the min/max loading margin approach. This allowed comparing the proposed solution to the peak/valley approach, as well as validating the later as a worst-case approach. The same test has been performed using demand data with variable and constant load share. In table 6.3.2, the number of the peak and valley scenarios, as well as maximum and minimum λ scenarios, are reported both for constant and variable load share.

	Peak	**Valley**	**min λ**	**max λ**
Constant load share	906	4275	906	4275
Variable load share	906	4275	762	4275

Table 6.3: Demand scenarios corresponding to peak, valley, minimum λ and maximum λ scenarios.

From table 6.3.2, a comparison between peak/valley and min/max λ approaches can be made for demand scenarios with constant and variable load share. On the one hand, peak and valley scenarios coincide for both constant and variable load share scenarios. The scenario of maximum loading margin coincide with the valley scenario for both constant and variable load share. Contrarily, it can be seen that, for variable load share scenarios, peak scenario does not coincided with the most critical one (minimum λ). This is worth emphasizing, since the use of a constant load share may obscure the real worst-case scenario.

A comparison between the results of the FACTS devices placement procedure using the peak/valley approach and the mean annual approach is presented next. Additionally, the results of the max/min λ approach are included. In figures 6.16 and 6.17, a representation of these results for demand scenarios with variable and constant load share is presented in order to enable a comparative analysis.

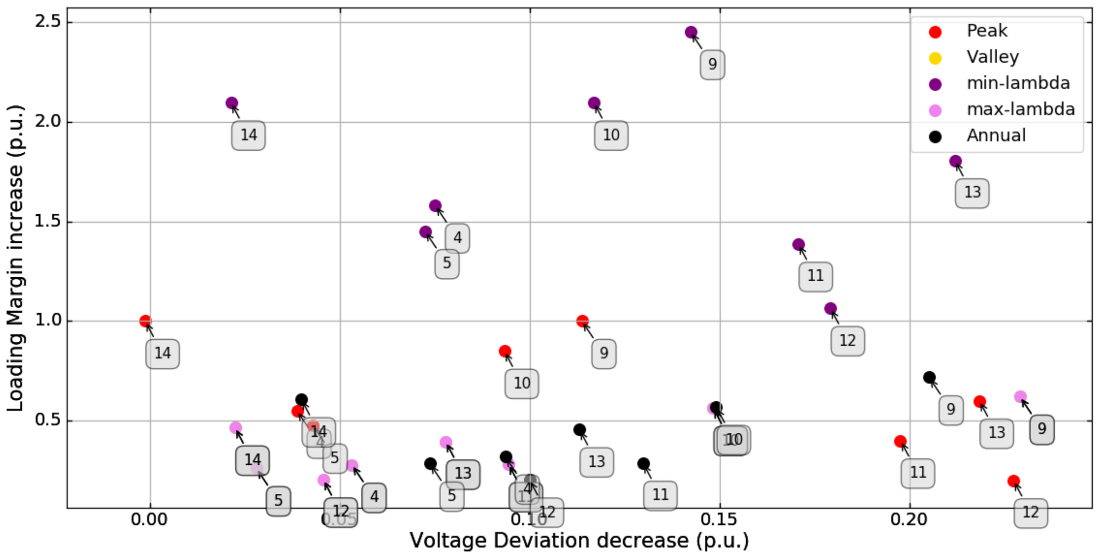

Figure 6.16: FACTS devices placement. Voltage deviation decrease versus λ increase for peak, valley, minimum λ and maximum λ scenarios. Comparison with mean annual values. Scenarios with variable load share.

The results obtained from the peak demand scenario with variable load share show substantial differences with the annual averaged result, especially in the case of loading margin increase. This leads to a change in the shape of the Pareto set, which includes buses 9, 12, 13 and 14 for peak scenario, while bus 9 is the only Pareto-optimal solution when mean annual results are considered.

Substantial discrepancies may be also found between peak results and the worst-case (minimum λ) results. The relative positions of the solutions and the range of the values taken by the loading margin index differ from one scenario to the next. In the case of minimum λ, the Pareto set is formed by buses 9 and 13. The valley and maximum λ scenarios coincide, so they are superimposed in the chart. It may be observed that mean annual results represent an intermediate solution between the peak/minimum λ scenarios and the valley/maximum λ scenarios.

In the case of constant load share scenarios, peak results and minimum λ scenarios are the same and thus provide identical results. These, however, show substantial differences with

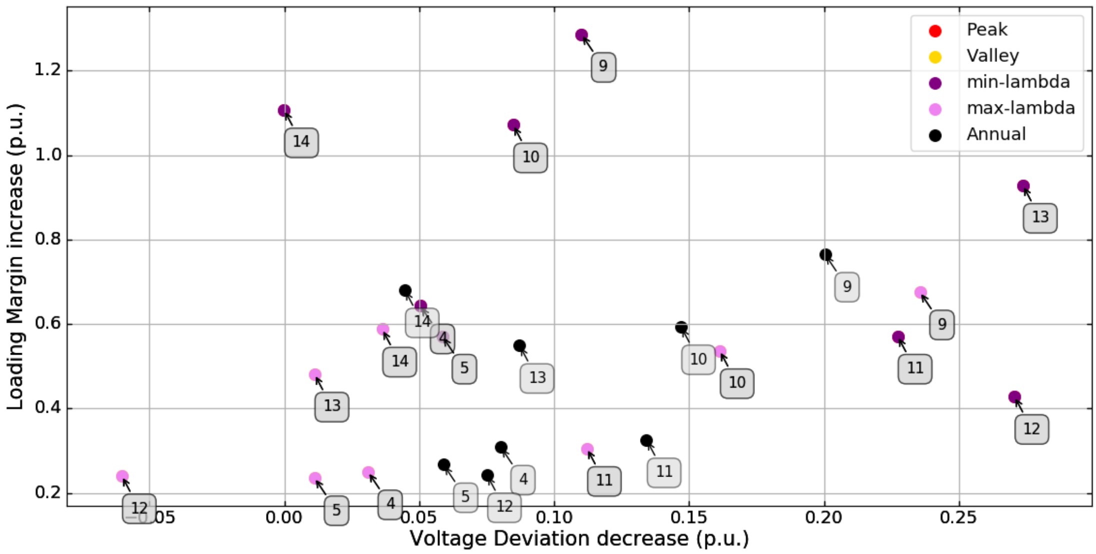

Figure 6.17: FACTS devices placement. Voltage deviation decrease versus λ increase for peak, valley, minimum λ and maximum λ scenarios. Comparison with mean annual values. Scenarios with constant load share.

respect to the annual averaged result as well. Results from valley and maximum λ scenarios coincide as well.

Again, the mean annual results seem to represent an intermediate solution between the peak/minimum λ scenarios and the valley/maximum λ scenarios. However, differences may be found in the Pareto set between the different approaches. For the mean annual approach, as well as for valley and maximum λ scenarios, the Pareto-optimal solution is bus number 9. In contrast, for peak and minimum λ approaches, the Pareto set is formed by buses 9 and 13.

Consequently, for variable load share scenarios, it is found that peak scenario does not coincide with the worst-case scenario. On the other hand, when demand scenarios' load share is constant, the worst case scenario is forced to be the peak scenario. Substantial discrepancies are found between averaged results and single-scenario results. More importantly, the FACTS devices placement decision seems to be sensitive to the approach used to select the demand scenarios.

Influence of Scenarios Selection Method on FACTS Devices Placement

The influence of loading level and load share on FACTS devices placement has been characterised in this experiment. Furthermore, a comparison between a single-scenario approach and a multi-scenario approach has also been performed. As a result, noticeable discrepancies between these two approaches have been found. Nonetheless, a great number of simulations have been performed so as to achieve these results. This, however, is a very inefficient method for assessing FACTS devices impact on power systems and their optimal placement.

It is beyond the scope of this study to find a solution to the creation of reduced representative data sets for power system analysis. Notwithstanding, a particular test has been performed on this detail and some clues have been found. This test is intended to compare two distinct methods for selecting demand scenarios for FACTS devices placement. On the one hand, different sets of demand scenarios were selected by randomly selecting different weeks from the data set. On the other hand, the same number of (hourly) demand scenarios were randomly selected one by one.

Subsequently, the two scenarios selection procedures are compared for a different number of scenarios, defined by weeks: namely, 1 week, 10 weeks and 20 weeks. In figures 6.18 and 6.19 this comparison is performed for scenarios with variable and constant load share, respectively. Mean annual values are also included in the chart for the sake of comparison.

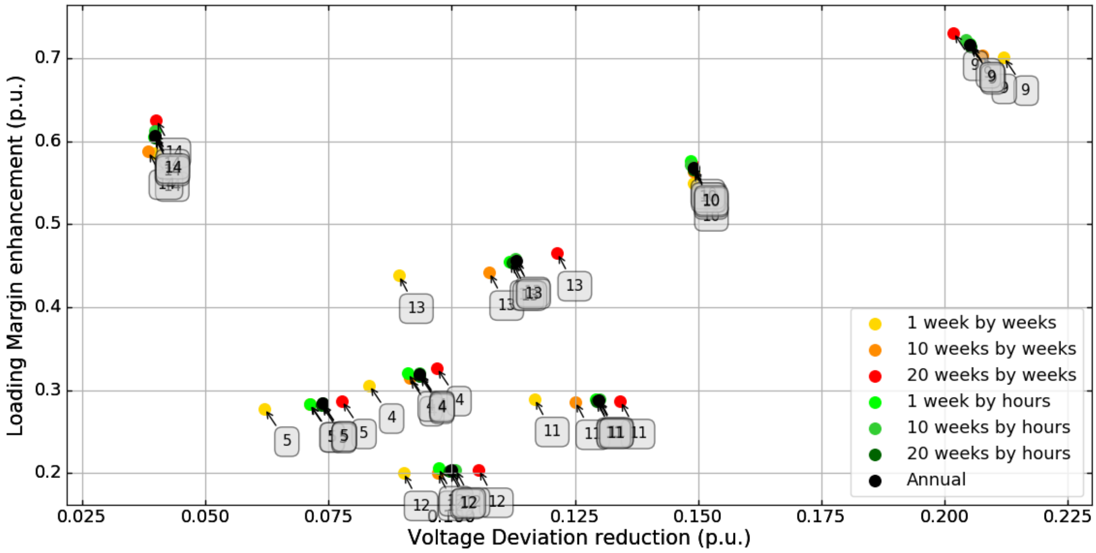

Figure 6.18: FACTS devices placement. Voltage deviation decrease versus λ increase for scenarios selected by hours and weeks. Comparison with mean annual values. Scenarios with variable load share.

For demand scenarios with variable load share, slight differences may be found between the mean annual values and the reduced data set. These differences, however, depend on the bus under consideration. It also may be observed that the results obtained from scenarios selected by weeks are further away from the annual mean than those obtained from scenarios selected by hours. This is particularly true for those referred to a single week. It is reasonable to think that, for a small number of samples, random samples best capture the average behaviour of the variable compared to samples that are concentrated in a concrete area of the search space.

Similar results have been found for demand scenarios with constant load share. In this case, the result from different scenarios selection methods tend to be more concentrated in some buses (9, 10, 11 and 14) and more disperse in others (4, 5 and 13). Results from scenarios selected by hours continue to be nearer the mean annual values.

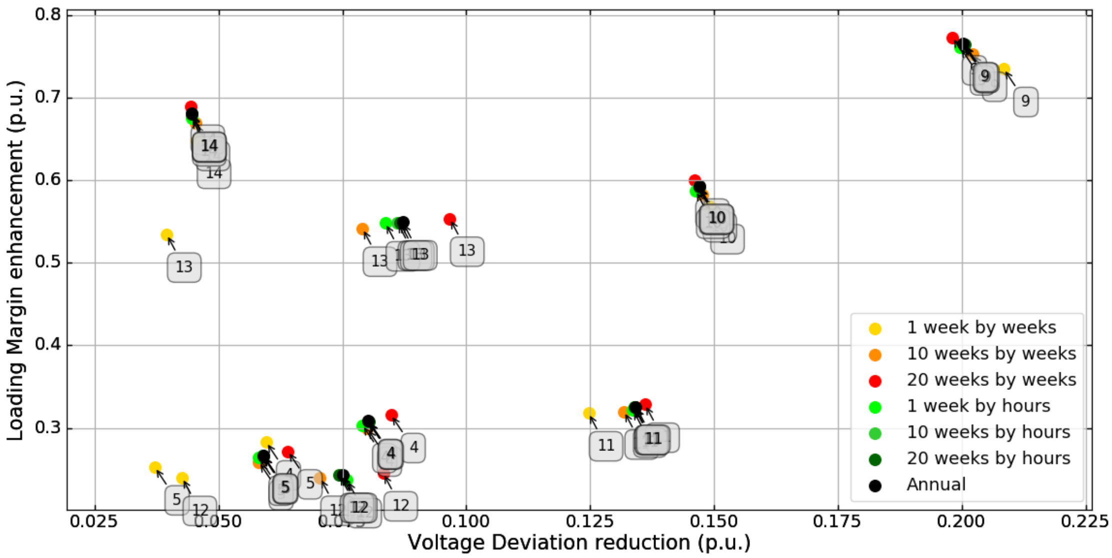

Figure 6.19: FACTS devices placement. Voltage deviation decrease versus λ increase for scenarios selected by hours and weeks. Comparison with mean annual values. Scenarios with constant load share.

In both cases, the sensitivity of loading margin increase and voltage deviation decrease to the scenarios selection method is small. Similarly, the sensitivity of the decision on the FACTS device location to this determinant is negligible. Nonetheless, this should not be interpreted as a refutation of the assumption that random demand scenarios creation may not adequately represent actual power system demand.

In this test, pre-defined disaggregated demand scenarios have been randomly chosen. Therefore, the coincidence of demand patterns of different nodes is accounted for by the original definition of the scenarios. This would not be the case of random demand scenarios creation methods, such as Monte Carlo simulation, unless specific rules and constraints are implemented to ”guide” the process.

In conclusion, reduced representative demand data sets may be created by randomly selecting pre-defined disaggregated demand scenarios. With a relatively small number of scenarios, good results may be obtained. A number of 1680 demand scenarios (10 weeks) proved to yield good results, while for 168 scenarios (1 week), some significant divergences are found with mean annual results, particularly for bus 13. Nonetheless, an exhaustive search may be performed to find the optimal number of scenarios.

6.3.3 FACTS Devices Control Configuration Using Distributed Data

Finally, once the optimal location for a FACTS device is found to be bus number 9, it is important to consider the influence of the voltage control reference on the device’s performance. As it will be shown, noticeable divergences may appear as a consequence of different reference values. With this in mind, an experiment focused on voltage control reference has been carried out.

For such an experiment, the device's location becomes a control variable. Taking advantage of the optimization procedure proposed for FACTS devices impact assessment, different values of voltage reference are tested using demand scenarios with variable load share. In this section, an analysis of the FACTS device's performance, focused on voltage control reference, is performed. The available solutions for voltage control reference value selection range from 0.98 to 1.05 p.u. in steps of 0.01 p.u..

In figure 6.20, the solutions of the optimisation problem are plotted in terms of voltage deviation decrease and loading margin increase. The Pareto front is also shown so as to find the optimal trade-off solutions.

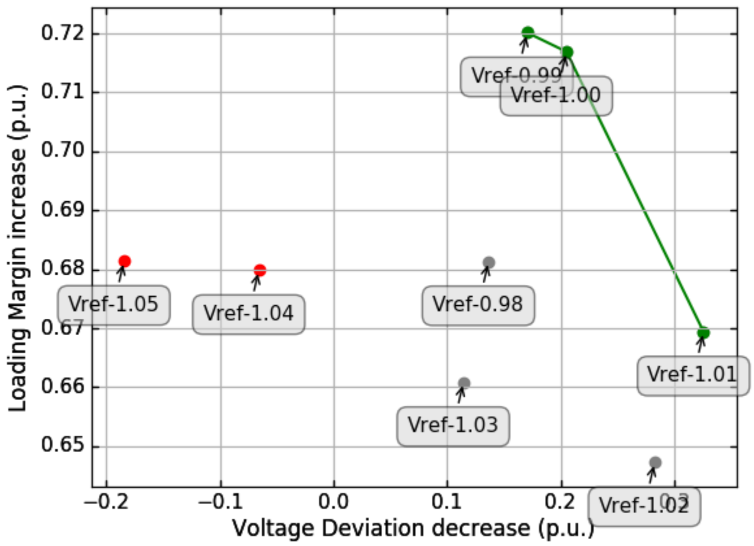

Figure 6.20: FACTS devices configuration. Voltage deviation decrease versus λ increase according to demand scenarios.

The results show that the solutions may be categorised into three different groups. On the one hand, control reference values above 1.04 p.u show negative values of voltage deviation decrease. This means that voltage profile is worsened when the FACTS device is provided with such a reference value. On the other hand, control reference values between 0.98 and 1.03 p.u. show positive values of voltage deviation decrease and loading margin increase. Among these solutions, the Pareto set is formed by solutions between 0.99 and 1.01 p.u..

A separate analysis of the results from both indices may provide useful insights. On the one hand, considering the increase of loading margin due to the FACTS device, it is interesting to see how reference values of 0.99 and 1.00 p.u. present noticeably better results. On the other hand, looking at voltage deviation decrease, it is important to note that reference values show a tractable tendency that has a turning point. Starting from 0.98 p.u., for every augment of the reference value, voltage deviation decrease augments. This means that, by augmenting the voltage control reference value, voltage deviation is reduced. However, once the reference value reaches 1.01 p.u., no more improvements on voltage deviation reduction are found. In fact, a quick deterioration of voltage profile is found as long as the voltage reference gets greater than 1.02 p.u..

Influence of Load Share on FACTS Devices Control Configuration

Given that several loading situations may occur during the operation of the FACTS device, it is important to take into consideration the influence of load share on the decision about the voltage reference value. With this in mind, and similarly to the FACTS devices placement study, demand scenarios have been classified into four quarters. These have been created based on the quartiles calculated from the ”flatness” of their load share profile (see section 6.3.2). The search for control reference values have been carried out for each quarter. Thus, voltage reference values have been evaluated for different types of load share profiles, from highly equally distributed demand scenarios (Q1), to highly unequally distributed ones (Q4). In figure 6.21, the results related to the studied voltage control reference values are plotted in terms of voltage deviation decrease and loading margin increase.

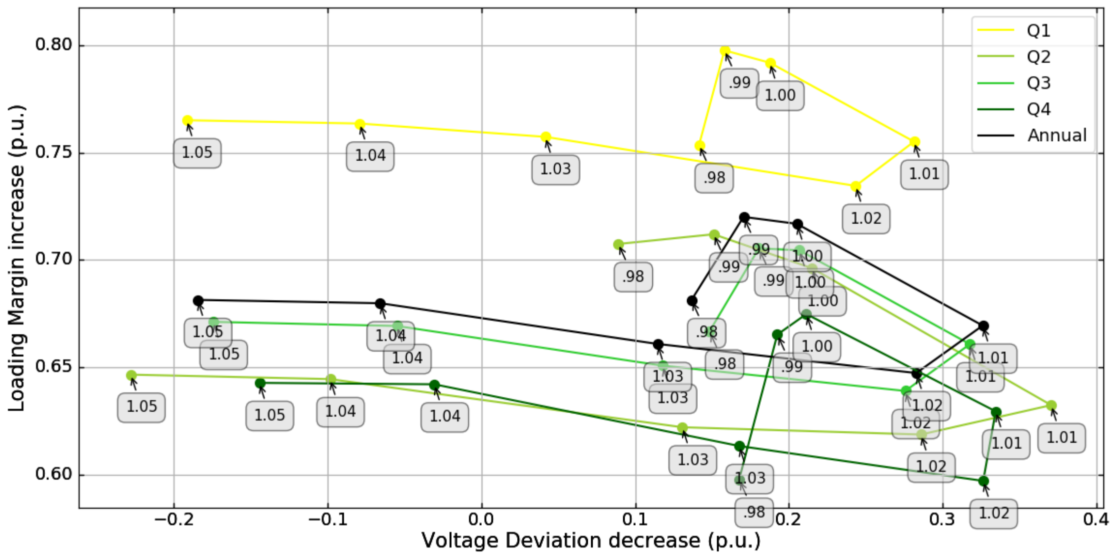

Figure 6.21: FACTS devices configuration. Voltage deviation decrease versus λ increase for demand scenarios as a function the load share flatness. Comparison with mean annual values. Scenarios with variable load share.

The results show that reference values above 1.03 p.u. provide negative values of voltage deviation decrease. The main effect of load share is to shift the solutions up or down inversely to the flatness of the load share profile. In other words, when the flatness of the load share profile decreases, the values of loading margin increase tend to augment for all solutions. This tendency can be also found in voltage deviation decrease, but in a more attenuated manner.

The variability of the results as a function of load share flatness is similar for all solutions. Variations of loading margin increase approach $0.12p.u.$, while variations of voltage deviation decrease range from $0.05p.u$ to $0.1p.u.$. As for FACTS devices' placement, mean annual values represent an intermediate solution with respect to those of the different quarters. Therefore, it may be observed that the influence of voltage control reference values on loading margin increase is considerable.

In general, the Pareto front is formed by the same solutions (0.99, 1.00 and 1.0 p.u.). Nonetheless, for Q4 demand scenarios, $0.99p.u.$ no longer belongs to the Pareto set. Thus, the decision on voltage reference value is sensitive to load share flatness.

Influence of Demand Scenarios' Total Power on FACTS Devices Control Configuration

In similar fashion, the effect of the demand scenarios' total power on the selection of the voltage control reference value has been analysed. Again, the quartiles are calculated based on the aggregated total power of each demand scenario so as to group them into four quarters. Then, the optimization procedure has been executed using demand scenarios from each quarter to search for the best reference values. Thus, voltage reference values have been evaluated for different types of demand scenarios as a function of their total power, from scarcely loaded demand scenarios (Q1), to highly loaded ones (Q4). In figure 6.22, the results related to the studied voltage control reference values are plotted in terms of voltage deviation decrease and loading margin increase.

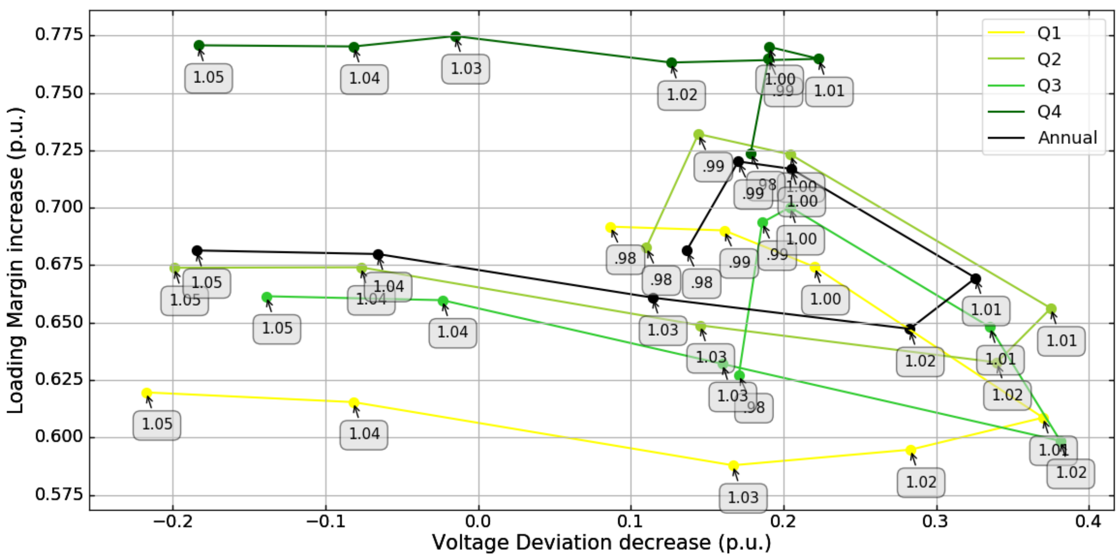

Figure 6.22: FACTS devices configuration. Voltage deviation decrease versus λ increase for demand scenarios as a function their total power. Comparison with mean annual values. Scenarios with variable load share.

The results show the influence of the scenarios' total power on loading margin increase and voltage deviation decrease for a FACTS device installed in bus number 9. In this case, loading margin increase tends to be directly proportional to the scenarios' total power. It can be seen that Q4 solutions show greater values than those from Q1 for loading margin increase.

In the case of voltage deviation decrease, a more detailed analysis needs to be performed. For high reference values (1.04 p.u. or above), the decrease of voltage deviation tends to increase as the scenarios' total power increases. In contrast, at this value, the decrease in voltage deviation seems to be inversely proportional to the scenarios' total power.

The variations of the results as a function of the scenarios' total power are greater and less homogeneous than those observed for load share flatness. Regarding voltage deviation decrease, these variations are smaller than $0.1p.u.$, except for reference values of 1.01 and 1.02 p.u.. In these cases, variations reach approximately $0.15p.u.$ and $0.25p.u.$ respectively, which means that, depending on the demand scenario, the improvement of the voltage profile may range from around $0.1p.u.$ to around $0.4p.u.$.

In terms of loading margin increase, two different sensitivities may be observed. On the one hand, the variations from one reference value to another as a function of the scenarios' total power range from $0.07p.u.$ to $0.1p.u.$. On the other hand, solutions from the same quartile show distinct variability as a function of the reference values. For instance, solutions from Q4 show a variability of $0.05p.u.$, while those from Q2 show a variability of $0.12p.u.$. Consequently, multiple sensitivities of the results have been found. Annual mean values always present a central position with respect to quartile-based values.

In terms of decision-making, the values between 0.99 and 1.01 p.u. are often included in the Pareto set (except for Q4). Nonetheless, reference values of 1.02 p.u. and 0.98 p.u., become Pareto-optimal for Q2 and Q1 respectively. Therefore, the decision on the voltage control reference value seems to be highly sensitive to the demand scenarios' total power.

Comparison Between Mean Annual and Peak/Valley Approach on FACTS Devices Control Configuration

Finally, the results obtained from the mean annual approach were compared to the peak/valley and min/max λ approach and a test was performed to validate the peak scenario as the worst-case scenario in terms of voltage collapse proximity. First, maximum and minimum load scenarios were searched. Then, taking the annual results of the test power system without the FACTS device, maximum and minimum loading margin scenarios were selected as well. Results of the peak/valley approach were compared to those of the min/max loading margin approach. This allowed a comparison between the proposed solution and the peak/valley solution. At the same time, peak scenario may be validated as the worst-case scenario. In figure 6.23, the results of the different approaches, for the studied voltage reference values, are graphically represented in terms of loading margin increase and voltage deviation decrease.

As previously mentioned, for demand scenarios with variable load share, peak scenario does not coincide with the worst-case scenario in terms of loading margin. Although, they present distinct results, particularly in regard to loading margin increase, and may be grouped together,

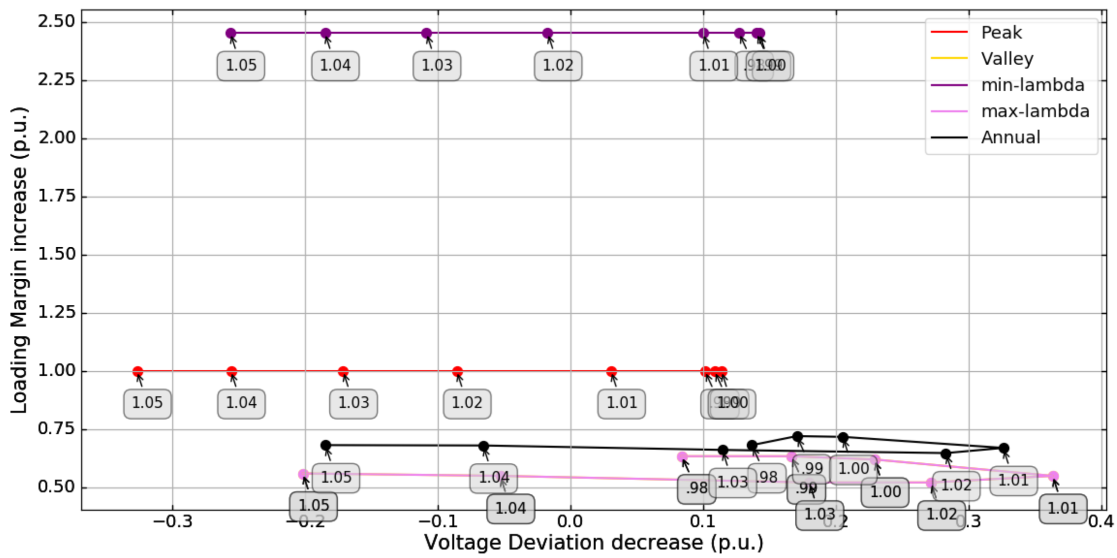

Figure 6.23: FACTS devices configuration. Voltage deviation decrease versus λ increase for peak, valley, minimum λ and maximum λ scenarios. Comparison with mean annual values. Scenarios with variable load share.

contrarily to mean annual results and valley and maximum λ scenarios. For peak and minimum λ scenarios, the reference values have almost no influence on loading margin increase. Focusing on voltage deviation reduction, reference values ranging from 0.98 p.u. to 1.00 p.u. show the best performance, with very similar results. On the other hand, results from valley scenario and mean annual results show a greater influence of voltage reference on loading margin increase. They also provide greater values of voltage deviation reduction, particularly for reference values between 0.98 and 1.03 p.u..

In terms of Pareto optimality, reference values between 0.99 and 1.01 p.u. are optimal. Interestingly, mean annual results for reference values of 0.98, 0.99 and 1.05 p.u. show greater values of voltage deviation decrease than peak/valley or min/max λ results, which seems contradictory with an (expected) averaged behaviour. Substantial discrepancies have been found between results obtained from a single-scenario approach, particularly from peak and min λ scenarios, and the mean annual approach.

Chapter 7

Conclusions and Future Work

In this chapter, the main conclusions and scientific contributions of this research are presented. The purpose of this work is to propose a methodology for FACTS devices impact assessment in power systems and, particularly, in small isolated power systems. With this aim, the main determinants affecting these problems have been studied. Different power systems performance indices have been compared and a method for index selection, based on the information they provide, has been developed.

From the literature review, different types of evidence have been found, and these have been used to design the research hypotheses and the proposed FACTS devices impact assessment methodology. After that, different experiments have been carried out to validate the research hypotheses and test the proposed methodology. From this research, useful conclusions for transmission expansion planning have been drawn and new unanswered questions have emerged, which could be the basis for future research.

7.1 Conclusions

In this section, the main ideas elaborated based on the literature review and analysis are presented prior to the discussion of the main results and conclusions of the experimental work.

A revision of the latest research on transmission systems expansion planning has provided an overview of the present situation. The adoption of market tools and the increase of renewable generators in power systems has changed the scope and requirements of transmission expansion planning. These changes are due to the interactions between the new generation units, including non-manageable generators, the new transmission infrastructures, the evolution of demand, etc., which forces us to take into account a greater number of demand and generation scenarios. In small isolated power systems this is even more important since they are more vulnerable to instability issues caused by demand and renewable generation power variations.

The revision of the most common techniques used for FACTS devices placement enabled us to find some ways in which they could be enhanced. One of the main limitations of FACTS devices placement procedures is that they are usually based on one or a few demand and/or generation scenarios. Similarly, TSOs usually base their analysis on the peak/valley approach, so they focus on studies that are also based on a reduced number of scenarios. As demonstrated in [26], in the presence of unmanageable renewable generators peak scenario may not be the adequate scenario for FACTS devices placement analysis. For this reason, it is important to include a sufficient number of demand scenarios so as to account for the interactions between different power systems elements.

Electrical demand may be studied as an aggregation of multiple loads, considering power system demand as the sum of the demanded power of the different substations or nodes. In [124], the authors have demonstrated that demand from different substations show specific characteristics. Consequently, the distribution of electrical demand between the different substations may change in time. It is important, for transmission expansion studies, to consider the interactions between demand patterns of different substations and between them and renewable generation patterns. In order to do so, it is necessary to analyse a sufficient number of disaggregated demand and generation scenarios.

When several demand scenarios are taken into account, three methods are commonly used for scenarios creation; namely, Monte Carlo simulation, load profiles and historical data. A literature review on these methods has been carried out, paying special attention to their capability to represent the actual and future demand behaviour. The main outcomes of this review are summarized below:

- Monte Carlo simulation is enabled to model the future behaviour of power system demand since it is based on probability density functions. Although common statistical software includes a wide range of random sample generation tools, they commonly generate independent samples, so additional methods are needed to generate correlated samples [142]. Consequently, results representativeness may not be ensured by Monte Carlo simulation unless it is provided with adequate rules and constraints to ”guide” the process of demand scenarios creation.

- Load profiles are found to be limited to represent ”past” demand, since they are derived from historical data and authors barely describe methods for representing future demand. The use of interpolation or extrapolation as a means for creating future scenarios would undermine the implications of new electrification technologies [153]. Furthermore, load profiles based exclusively on overall electricity demand may not properly represent seasonal variations in demand patterns [133]. Although a great deal of work has been done to classify demand patterns as load profiles, a little has been done to build demand scenarios from them [129]. Consequently, we have found that simulation-ready load profiles barely exist and, when they do, it is difficult to assess their actual representativeness.

- Historical data provides detailed information of power systems demand. It also adequately represents the interactions between different variables, since they are time series based on real data. However, this data cannot be reliably used to represent future situations [153]. In addition, representativeness is guaranteed only for the power system from which data was measured. Demand data from a given power system may not provide reliable demand scenarios to be simulated in a distinct power system simulator. This is especially important if demand is analysed in a disaggregated manner.

Regarding FACTS devices impact assessment, many different objective functions have been used. In this sense, voltage stability objective functions are the most common, followed by costs and transmission losses [9]. Recently, social welfare and environmental objectives functions have been used [3]. Nevertheless, indices are not usually selected in a systematic manner but by heuristic procedures based on experience and expertise of system planners and researchers. Index selection based on systematic procedures may provide a more generalizable solution that may also consider the interactions between the different variables [49].

An interesting tool for index selection is *feature selection*. In machine learning and data mining, feature selection is used to find the smallest feature subset which provides the most comprehensive information about a system or process [56]. A frequent method for feature selection is mutual information (MI), which is based on information theory. The MI measures the amount of information that a certain variable, index or feature shares with another [56]. In this study, the MI is used to find those indices that share less information and thus provide the most complementary information about the problem.

In this research, an experiment has been performed to evaluate the influence of load share on the FACTS devices placement problem and two experiments have been carried out to test the different research hypotheses. The main conclusions extracted from the results analysis are presented next.

7.1.1 Effect of Load Share on FACTS Devices Placement

The first experiment was designed to investigate the influence of load share in FACTS devices placement studies. With this aim, the method proposed in [101] was modified and applied to the IEEE 14-bus test system to estimate the FACTS device (STATCOM) optimal location. Several demand scenarios, with the same total power and distinct load share, were created so as to iteratively run the FACTS placement process.

This study has revealed that load share may be considered in order to ensure a robust result when dealing with power system planning studies. Moreover, the selected objective function is also found to affect the decision on FACTS devices placement.

The experiment has led us to the general conclusion that load share has a major influence in FACTS devices placement. Depending on the objective function, the optimal solution differs. The FPI provides bus 13 as the most frequent choice, while λ determines that bus 12 is the most preferred one. Nonetheless, in spite of the objective function used, it is found that:

A The weakest buses were more frequently selected.

B The preferred buses were inside, or in the vicinity of, the most loaded areas.

Since this methodology is based on typical power system parameters (loading margin, voltage and reactive power losses), these findings may be generalised to other power systems and be useful for researchers and power system planning facing the task of FACTS devices placement. Given the influence of load share on FACTS devices placement, the results support the idea that the system demand peak may not be the best choice as a base case for these studies [26]. Moreover, studying a single system configuration may not be enough to ensure a robust solution.

7.1.2 FACTS Devices Placement Using Distributed Data

The second experiment was aimed at testing the proposed FACTS devices placement methodology and validating the first research hypothesis. The proposed methodology was based on the performance indices' *mean relative improvement* and includes a decision-making procedure based on Pareto optimality. Historical distributed data was used to create 8760 demand scenarios with a variable demand distribution and an index selection method was used to choose the indices that would be used for FACTS devices placement.

The index selection method showed results that are consistent with the existing literature. Loading margin and voltage deviation were selected as the indices providing the most heterogeneous information. From the literature review, voltage stability indices have been found to be used by researches in most FACTS devices placement studies [9].

The proposed methodology identified bus number 9 as the best FACTS device location. This is consistent with previous studies which showed that, when FACTS devices placement is based on the search for the best location for compensation, instead of searching for the weakest bus, bus 9 is preferred ([101] and [21]).

Different sets of demand scenarios have been used to evaluate the results' sensitivity to variations in power system's demand. The proposed methodology has been provided with sets of demand scenarios with different load share. As a result, the FACTS device could be optimally placed under different load distribution characteristics, from highly equally distributed scenarios, to highly unequally distributed ones. Bus 9 proved to be the best solution independently of the demand scenarios. Therefore, it may be concluded that, although voltage deviation decrease and loading margin increase are sensitive to load share flatness, the placement decision is robust in terms of load share variations if enough demand scenarios are considered.

In order to analyse the implications of load share variations in detail, two sets of demand scenarios with different load share characteristics were created, based on historical data. On the one hand, a set of scenarios was created using the original load share calculated from the historical data. On the other hand, a set of scenarios was created using a constant load share. These sets of scenarios were used for identical tests whose results are presented below, specifying whether they refer to demand scenarios with variable or constant load share.

The influence of the demand scenarios' total power has also been studied. Distinct sets of scenarios were created by grouping scenarios according to their total power, from scarcely loaded scenarios to highly loaded ones. The results of the FACTS placement procedure are found to be sensitive to variations in demand scenarios' total power. Nonetheless, these sensitivities differ from one particular solution (location) to another. It is found that decision-making is also sensitive to changes in demand scenarios' power, since the shape and composition of the Pareto front may differ for highly loaded demand scenarios. Results from demand scenarios with variable load share are found to be slightly different from those of constant load share. However, no significant differences are found in this regard.

Mean annual results have been also compared to the worst-case scenario results. To this end, the search for FACTS devices best placement has been carried out for maximum and minimum demand scenarios (peak and valley) and for maximum and minimum loading margin scenarios. In order to select the scenarios of maximum and minimum loading margin, annual results have been taken from the study in which the simulator does not include the FACTS device, and those scenarios with greater and smaller loading margin have been selected. This has been done for demand scenarios with constant and variable load share. Results show that, when a variable load share is used, peak scenario do not coincide with the minimum λ scenario. Therefore, peak scenario may not represent the real worst-case scenario and constant load share scenarios may hide it. Substantial discrepancies are found between averaged results and single-scenario results, both in regard to the indices' values and in relation to the final decision.

Finally, different demand scenarios selection methods were tested. On the one hand, sets of scenarios were selected by weeks. On the other hand, an equal number of scenarios were individually selected. The results show that reduced representative demand data sets may be created by randomly selecting demand scenarios individually. Since the pre-defined demand scenarios were created from distributed historical data, they respect the coincidence of demand patterns from different load buses. Therefore, with a relatively small amount of scenarios, good results may be obtained. A number of 1680 demand scenarios (10 weeks) turned out to provide good results, while for 168 scenarios (1 week), some significant divergences are found with mean annual results. Nonetheless, an exhaustive search may be performed to find the optimal number of scenarios.

Results show that the sensitivity of FACTS devices placement to demand scenarios total power and load share needs to be considered. A variable distribution of load share needs to be accounted for so as to ensure robust results, specially if a peak/valley approach is used. Therefore, this experiment has enabled us to validate the first research hypothesis that guided this study, which is:

- **Hypothesis 1:** Considering a greater number of demand scenarios with a variable load share among the different buses may provide better results in FACTS devices placement studies.

Additionally, the ability of the proposed methodology to account for demand variations in FACTS devices placement has been demonstrated.

7.1.3 FACTS Devices Control Configuration Using Distributed Data

The third experiment was aimed at investigating the implications of demand variations in FACTS devices voltage control reference selection. The proposed methodology has been used to evaluate the efficacy of different voltage control reference values.

Results have demonstrated that loading margin increase showed a highly non-linear behaviour, providing much greater values for certain reference values (0.99 and 1.00 p.u.). In terms of voltage deviation decrease, reference values above 1.03 p.u. showed negative values, meaning that they worsen voltage profile. More interestingly, analysing the tendency of the results as a function of the reference values, a turning point is found at 1.01 p.u.. Up to that value, the increase of the reference value yield to a reduction of voltage deviation, while higher reference values provide an increase of voltage deviation in an accelerated manner. The Pareto-set is formed by reference values ranging between 0.99 and 1.01 p.u..

An inverse relationship is found between demand scenarios' load share and loading margin increase caused by the FACTS device operation, disregarding the voltage reference value. This behaviour is also found, in an attenuated manner, in voltage deviation decrease. The Pareto set has been proven to change depending on the quarter being studied. Thus, it is found that decision-making on voltage reference value selection presents a remarkable sensitivity to load share variations.

A direct relationship is found between demand scenarios' total power and loading margin increase. It is also found that, for high reference values, voltage deviation decrease tends to augment when demand scenarios' total power increases. For small reference values, the decrease of voltage deviation seems to be inversely proportional to demand scenarios total power. Results show that loading margin increase augments when demand scenarios total power augments, independently of the voltage reference value. Demand scenarios' total power proved to have a strong influence on the Pareto set, leading to frequent changes of Pareto-optimal solutions. Consequently, the decision on voltage control reference value is found to be highly sensitive to loading level.

It is also found that, for the peak scenario, loading margin increase take values near to 1.00 p.u., while these values approach to 2.5 p.u. when the minimum λ scenario is analysed. For both scenarios, the influence of voltage control reference value on loading margin increase is negligible. Regarding to voltage deviation decrease, for both scenarios, solutions between 0.98 and 1.00 p.u. present the best results. Mean annual results demonstrated to be very similar to those of valley scenario. Both scenarios show a greater variation of the indices' values as a function of voltage reference values, but the Pareto-set is formed by reference values between 0.99 and 1.01 p.u..

The proposed methodology has shown good results when it is used for voltage control reference value selection. The best rated values are those near to 1.00 p.u., so the results are coherent with the expectations. Furthermore, this methodology has demonstrated to be able to capture the results sensitivities to variations in demanded power and load share. The implications of these sensitivities need to be considered in FACTS devices voltage control reference value selection.

For these reasons, it may be considered that this experiment has enabled us to validate the hypotheses related to voltage control performed by FACTS devices, which are:

- **Hypothesis 2:** The reference value influences the effectiveness of the voltage control performed by FACTS devices.

- **Hypothesis 3:** Considering a greater number of demand scenarios with a variable load share among the different buses may provide better results in FACTS devices configuration studies.

Furthermore, the suitability of the proposed methodology for selecting FACTS devices voltage control reference values, attending to load variations, has been demonstrated.

7.2 Main Contributions

The literature review and the experimental work has permitted to provide some contributions related to FACTS devices impact assessment. The main scientific contributions of this research are described in this section.

1. In chapter 2, the problem of FACTS devices placement has been analysed. A review of the main techniques and approaches used to solve these problems has enabled us to demonstrate that it is not common to consider a significant number of scenarios. Some research works have demonstrated that the weakest bus in terms of voltage stability may not be the optimal solution for FACTS devices placement. Additionally, it has been found that peak demand scenario may not ensure the best results.

2. In chapter 3, the main demand scenarios' creation techniques have been revised in the context of transmission expansion planning, and an overview of the characteristics of electrical demand as a disaggregated feature has been provided. Some new determinants of power systems' analysis have been described, and the need for enhanced electrical demand modelling techniques has been found. It has been also found that disaggregated data sets are infrequent, and that methods intended to generate disaggregated demand scenarios are uncommon. A part of the ideas described in this chapter were published in the paper *"Power System Planning Supported by Big Data"*, in European Simulation and Modelling Conference, 2018 [119].

3. In chapter 4, theoretical proof of the influence of load share on FACTS devices placement is provided. Based on power systems' equations, a simplified model of a power system with a reactive power compensation has been designed to account for demand variations. The influence of load share on the compensator optimal placement has been theoretically demonstrated. This contribution was published in the paper *"A FACTS Devices Allocation Procedure Attending to Load Share"*, in Energies, 2020 [165].

4. In chapter 5 a methodology for FACTS devices impact assessment considering demand variations is proposed. This methodology is based on the *mean relative improvement* of various performance indices, and Pareto optimality is used for decision-making. This methodology includes a proposal for index selection based on mutual information. The development of this methodology, as well as the results obtained, are included in a scientific paper that will be submitted for publication soon.

5. In chapter 6 the effectiveness of the proposed methodology to account for demand variations is verified for both FACTS devices placement and voltage control reference value selection. The influence of load share and loading level on FACTS devices placement and configuration is proved using historical distributed demand data. Additionally, substantial discrepancies have been reported between the traditional peak/valley approach and the proposed solution, which is based on averaged results. It is found that, for demand scenarios with variable load share, peak scenario may not be the worst-case scenario. It is important to note that this methodology may be generalised to analyse other transmission expansion planning problems, such as renewable generators placement, given that it is not based on any particular assumption. It is our intention to include the results provided by this methodology applied to renewable generators placement in a scientific paper in the near future.

6. In chapter 6 the proposed index selection method has been validated. The proposed method is based on mutual information and has provided a solution that is consistent with the preferences of experts and researches according to the literature review. It is also important to note that this method may be used for index selection in different problems, since it is based on the information they share from a statistical perspective. It is our intention to include the development of this method, as well as the results obtained, in a scientific paper that may be submitted for publication soon.

7.3 Publications

Different publications have resulted from this research work. Particularly, a research article has been published on a indexed scientific journal. These publications are presented subsequently:

- *A FACTS Devices Allocation Procedure Attending to Load Share*

  - **Authors:** Marrero Vera, S.; Nuez Pestana, I.; Hernández Tejera, M.
  - **Journal:** Energies
  - **DOI:** https://doi.org/10.3390/en13081976

- *Optimising Power Systems by Automating Large Sets of Simulations*
  - **Authors:** Marrero Vera, S.; Reyes Sanchez, T. D.; Évora Gómez, J.; Hernández Cabrera, J. J.
  - **Congress:** European Simulation and Modelling
  - **Place:** Bourdeaux, France
  - **Date:** 2020

- *Power System Planning Supported by Big Data*
  - **Authors:** Marrero Vera, S.; Évora Gómez, J.; Hernández Cabrera, J. J.
  - **Congress:** European Simulation and Modelling
  - **Place:** Ghent, Belgium
  - **Date:** 2018

- *Problemática en la ubicación de dispositivos FACTS en los sistemas eléctrcios de potencia*
  - **Authors:** Marrero Vera, S.; Nuez Pestana, I.; Hernández Tejera, M.
  - **Congress:** XXXIX Jornadas de Automática
  - **Place:** Badajoz, Spain
  - **Date:** 2018

- *Ensayo experimental con supercondensadores para su utilización como sistema de almacenamiento de energía*
  - **Authors:** Marrero Vera, S.; Ramos, A.; Quintana, J. J.; Nuez Pestana, I.
  - **Congress:** XXXIX Jornadas de Automática
  - **Place:** Badajoz, Spain
  - **Date:** 2018

7.4 Future Work

In the course of the development of this research, multiple promising questions and approaches have emerged. Some of them could not be assessed in this study because of space and focus, but they may facilitate the continuation of this research with some future work. Therefore, we consider some of these issues are worth highlighting due to their interest for future research. These future research topics are outlined below.

1. **Analysis of the suitability of the FACTS devices assessment methodology for different purposes:** the proposed methodology has proven its suitability for FACTS devices placement and configuration. Nonetheless, it may be used to assess other transmission expansion planning problems. The analysis of the performance of this methodology on different problems, such as renewable generators placement and/or configuration, should be faced in future researches.

2. **Inclusion of artificial intelligence as a means for enhanced results:** Artificial intelligence techniques are frequently used for FACTS devices impact assessment with good results. The design of the proposed methodology makes it compatible with such techniques, so they may be implemented with relatively little effort in future research projects.

3. **Analysis of the suitability of the index selection method for different purposes:** as previously mentioned, since it is based on mutual information, the proposed index selection method is independent of the field and scope of the problem under analysis. Therefore, its suitability and effectiveness in different contexts may be investigated.

4. **Analysis of multiple FACTS devices placement and methodology proposal :** this research is focused on the optimal placement of a single FACTS device. Nonetheless, a greater number of devices may be jointly placed for enhanced compensation. Moreover, FACTS devices of different types may be concurrently placed to tackle distinct power systems issues at the same time. This new research scope entails new complexities due to interactions between FACTS devices and combinatorial issues related to simulation and data management.

5. **Joint optimisation of FACTS devices placement and configuration:** in this research, the optimal placement and configuration of a FACTS device have been independently addressed. Nonetheless, it would be of interest to jointly evaluate FACTS devices placement and configuration to consider their possible mutual influence.

6. **Voltage control reference based on zonal data:** the voltage reference value may be set as a function the voltage on FACTS device's surrounding area, given that its influence is mainly local. By doing so, the controller could take into account the consequences of its control actions over its whole area of influence. Such a solution could be evaluated taking advantage of the proposed methodology.

7. **Analysis and methodology proposal for enhanced demand scenarios creation:** in this research the need to consider demand variations in transmission expansion planning analysis has been reported. Load Profiles may enable a disaggregated demand scenarios creation method that enhances demand representation. This conclusion may serve as the basis for future research projects.

Appendix A

Sensitivity Analysis of the MI-based Metric

As argued in chapter 5, the approach used for indices selection is based on the concepts of entropy and mutual information, in the context of the information theory. Therefore, the calculation of the entropy, and particularly the joint entropy, is crucial to ensure a good performance of the indices selection method. In order to compute the entropies, it is necessary to know the probability density distribution of every variable. Additionally, in the case of the joint entropy, it is also necessary to know the joint probability density distribution of every combination of two variables. Given that the data used to represent the behaviour of each index derive from a sample of the actual distributed power system demand, its density distribution is unknown. Therefore, a probability density estimation method needs to be implemented.

In this context, histograms may be used as a simple and efficient method for probability density estimation. Histograms discretise the range of values that the variable takes so as to provide a piece-wise estimation of the probability density. With this aim, the range of the variable is divided into a certain number of interval or ”bins” and the amount of values that fall into each interval is accounted. This method is relatively simple and effective. Nonetheless, there are some issues that may affect the accuracy of the results. The main ones are related to the number of bins, also termed as quantums, denoted by (Q). Unfortunately, we found no appropriate method to select an optimal number of bins in the literature review. Consequently, an iterative process has been carried out to search for the value of Q that ensures a robust result. This section is intended to describe this process.

Some assumptions have been made and need to be considered. Firstly, given that different variables may have significantly different ranges of values, the variable range method has been used. By doing so, a particular size of the bin is specified as a measure of the ”granularity” of the estimation. Then, the number of bins is calculated for each variable based on the specified granularity. So as to prevent the algorithm from making estimations with an insufficient number of bins, a minimum value of Q needs to be also specified. Therefore, the accuracy of the estimation relies on the granularity and minimum value of Q. Granularity is specified in the same magnitude as the variable whose probability density is to be estimated. In this research, granularity is specified *per unit*.

In order to find the values of these variables that ensure a robust result, different combinations of them have been tested. Simulations have been carried out and the $D-distance$ has been calculated for every pair of indices based on the predefined values. Consequently, a sensitivity analysis of the $D-distance$ to these variables is performed. The goal of this study is to find the range of values for which the $D-distance$ no longer depend on the variables under study. In figures A.1, A.2 and A.3, the values of D for different values of granularity are presented for minimum values of Q of 20, 40 and 60 bins respectively. In the charts, values of the $D-distance$ between different pairs of indices are represented by different colors.

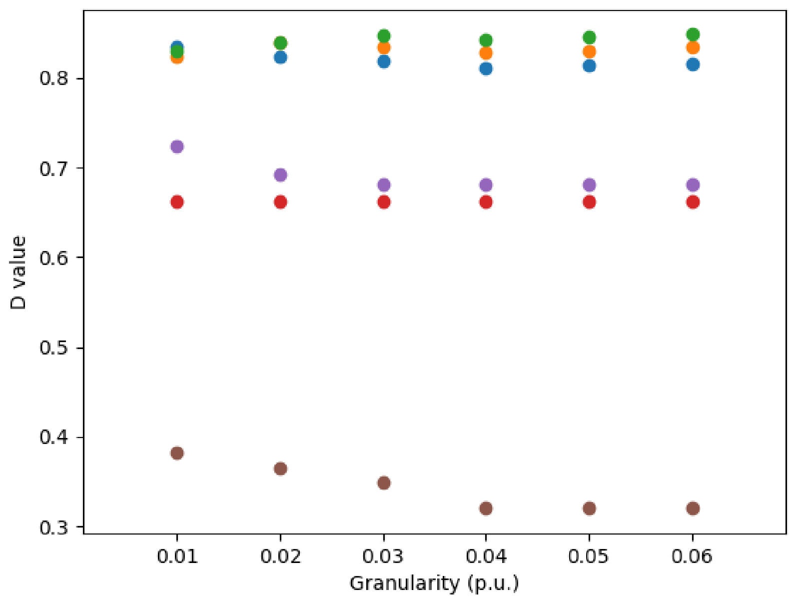

Figure A.1: D-distance versus granularity for a minimum number of bins of 20.

It can be seen that the values of D show a significant sensitivity to the granularity of the estimation. This, however, is attenuated when the minimum allowed value of Q augments. However, for a minimum allowable Q of 20 bins, some oscillations of the distance values are observed. It is worth noting that, in general, the D metric tends to stabilise for values of granularity above 0.04. Therefore, in such a situation, D seems to become independent of the granularity. For this reason, granularity has been set to 0.04 and the minimum allowed number of bins has been set to 40.

In this respect, a relevant consideration is worth emphasizing. The dynamic calculation of the number of bins is based on the range of values that each variable takes, since it is the ratio between the variable's range and the pre-defined granularity. Therefore, the number of bins is strongly affected by the presence of "outliers", which may significantly condition the variable's range. In this research, the input data is the historical demand data, so these outliers should not

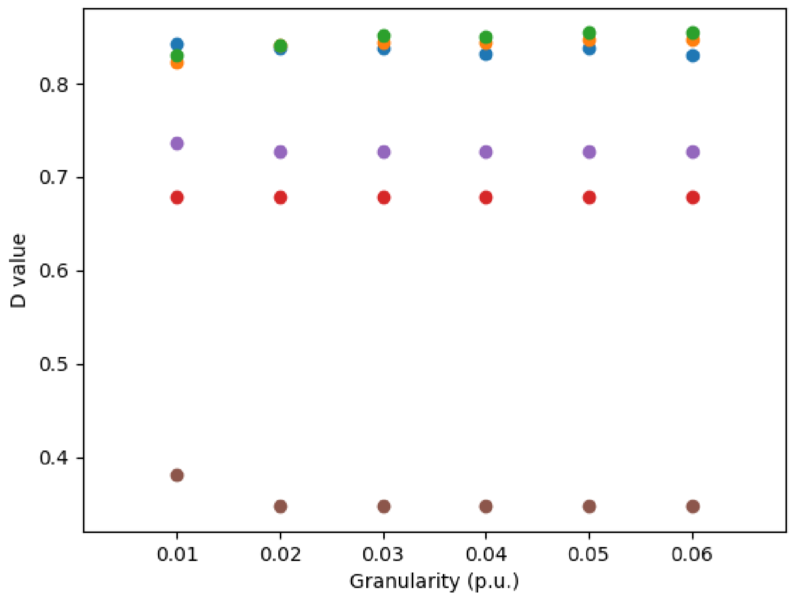

Figure A.2: D-distance versus granularity for a minimum number of bins of 40.

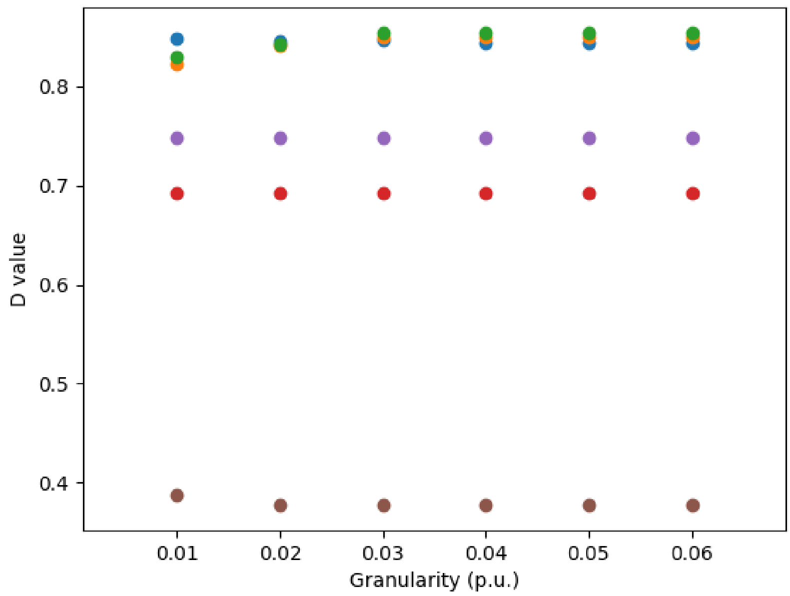

Figure A.3: D-distance versus granularity for a minimum number of bins of 60.

be considered as singularities of stochastic process. In contrast, they should be considered as an infrequent, but feasible, operation scenario. Input data has not been processed so as to eliminate or correct datum that may be significantly distinct to the average values.

Appendix B

Resumen en español

Esta investigación se ha llevado a cabo en el contexto de la realización de una Tesis Doctoral dentro del programa de doctorado en Tecnologías de Telecomunicación e Ingeniería Computacional de la Universidad de Las Palmas de Gran Canaria. El objetivo de esta investigación es proponer una solución a la evaluación del impacto de los dispositivos FACTS en los sistemas eléctricos en base a información distribuida para mejorar la robustez de los resultados. Con este objetivo se han analizado los principales condicionantes de estos problemas. Esta propuesta metodológica ha sido probada tanto para la ubicación de dispositivos FACTS como para la selección de la referencia del control de tensión. Se ha prestado especial atención a la problemática de los Sistemas Eléctricos de Potencia (SEP) pequeños y aislados, dadas los particulares problemas de estabilidad que presentan.

B.1 Introducción

En los últimos años, los SEP en la Unión Europea, y particularmente en España, han sufrido una importante transformación que ha cambiado la forma en la que éstos son gestionados. La progresiva tendencia hacia un sistema de gestión basado en el libre acceso a las infraestructuras de transmisión ha acarreado una serie de transformaciones relevantes. En los sistemas eléctricos liberalizados, múltiples actores con diversos objetivos, muchas veces contrapuestos, interactúan a través de herramientas de mercado. En este contexto, las redes eléctricas deben asegurar intercambio de energía entre generadores y consumidores, pero también la competencia entre los distintos actores [1].

Recientemente se ha producido un aumento significativo de generadores basados en fuentes de energía renovable (RES) en los SEP, donde las fuentes renovables han alcanzado un peso relevante en la generación eléctrica, pasando del 14,3% al 30,7% de la potencia generada entre los años 2004 al 2017 [13]. La evolución de estas tecnologías ha hecho que estos generadores sean económicamente competitivos frente a los generadores convencionales. Los generadores renovables no emiten gases de efecto invernadero durante su operación, pero adolecen de algunas limitaciones que hacen que puedan perjudicar la estabilidad de los SEP. La no gestionabilidad de las RES genera nuevos retos para garantizar todos los objetivos que se han de cumplir en la generación eléctrica [14]. La transición de los sistemas eléctricos de potencia convencionales hacia sistemas con un peso importante de RES aumentará la complejidad de la operación de los mismos.

Los sistemas eléctricos aislados presentan, de forma inmediata, los problemas de un incremento de la penetración de las RES. Estos sistemas poseen ciertas características que los hacen especialmente vulnerables en términos de estabilidad. La generación eléctrica convencional en sistemas aislados suele tener unas características de operación muy restrictivas, que no son compatibles con las oscilaciones de potencia instantánea que generan las RES. En cuanto a las redes de transporte, estas suelen ser poco malladas, y por consiguiente las oscilaciones de fuentes renovables repercutirán en mayor grado en su estabilidad [16]. Mientras que en los sistemas eléctricos continentales se está incrementando la cantidad de potencia de origen renovable, mejorando los efectos medioambientales y los costes en la generación, en los sistemas pequeños y aislados empiezan a observarse los límites de esta integración.

El incremento de la generación renovable y la liberalización de los sistemas eléctricos han provocado cambios en las herramientas de análisis utilizadas por los operadores de SEP. Las nuevas instalaciones renovables tienen una influencia decisiva en la planificación de la red de transmisión. Por este motivo, los procedimientos tradicionales para la planificación, han sido modificados para incluir estos nuevos generadores, así como sus interacciones con la demanda [3]. Sin embargo, las incertidumbres de las RES junto con la necesidad de nuevas infraestructuras eléctricas para incorporar la potencia renovable a los sistemas eléctricos son parte de la integración que aún no están totalmente resueltas [3]. Los operadores de sistemas eléctricos (TSO, por sus siglas en inglés) deberán continuar realizando cambios en los procedimientos de operación para introducir la casuística de los nuevos generadores en su análisis [15]. En estas circunstancias, se hacen necesarias nuevas herramientas de análisis que tengan en cuenta un mayor número de escenarios de demanda y generación renovable, particularmente en los SEP pequeños y aislados.

Se prevé que los sistemas eléctricos deban reforzar la seguridad del suministro, logrando precios de la electricidad asequibles y competitivos, permitiendo una mayor integración de RES, y teniendo en cuenta un impacto medioambiental asumible [2]. Se espera un crecimiento más moderado del consumo de la energía eléctrica en los próximos años, mientras que millones de nuevos consumidores podrán producir su propia electricidad de forma local a través de la red [18]. Esta situación obligará a afrontar nuevos retos como la congestión de líneas, los flujos de potencia inversos y las oscilaciones de potencia, que serán más frecuentes e importantes. Sin embargo, los procesos de expansión de las redes eléctricas se están enfrentando a dificultades legales y administrativas que los retrasan y, en ocasiones, impiden su ejecución [19]. Estas dificultades suelen estar relacionadas con el impacto ambiental de las nuevas infraestructuras y el uso del territorio.

En la década de 1980 se diseñaron los primeros Sistemas Flexibles de Transmisión en Corriente Alterna (FACTS) con el objetivo de mejorar la transmisión eléctrica. Los dispositivos FACTS son dispositivo basados en la electrónica de potencia diseñados para proporcionar control, de manera flexible, de uno o varios parámetros de la red [20]. De este modo, es posible mejorar el flujo de potencia por las redes, y en consecuencia la estabilidad de los SEP. Estos dispositivos han llegado a ser especialmente efectivos en el control de tensión, la gestión de flujos de potencia, la cancelación de armónicos, la reducción de perturbaciones, el equilibrado de cargas, etc. [10]. En esta investigación, nos centraremos en sus capacidades para proporcionar control de tensión, en particular, desde el punto de vista del análisis en régimen permanente.

B.2 Ubicación de dispositivos FACTS en sistemas eléctricos de potencia

El efecto de la compensación de reactiva, en la que se basan principalmente los FACTS, es intrínsecamente local, ya que se atenúa con la distancia respecto del compensador. Esto hace que la ubicación y configuración óptimas de los dispositivos FACTS sea crucial para su efectividad en el control de tensión. Además, la elevada inversión que suelen requerir estas soluciones exige utilizar estos dispositivos de la manera más eficiente posible. No obstante, diversos estudios han demostrado que el análisis del impacto de los dispositivos FACTS sobre los SEP es un problema complejo. No basta con determinar el nodo más débil del sistema, ya que este no siempre proporciona la mayor efectividad de los FACTS [21], y es necesario tener en cuenta la influencia de múltiples variables. En este estudio, nos centraremos en los efectos que tienen las variaciones de la demanda en este problema.

Los estudios sobre el impacto de los FACTS en los sistemas eléctricos suelen centrarse en la búsqueda de su ubicación, tipo y tamaño óptimos [10]. Por otra parte, la sintonización de los controladores de los FACTS para conseguir una dinámica adecuada ha sido estudiada en diversos trabajos ([22], [23] y [24]). Si bien, también es necesario seleccionar adecuadamente el valor de consigna con el que se configura el controlador. Para el análisis en régimen permanente, la selección de la referencia de tensión puede ser analizada usando las mismas herramientas empleadas para la ubicación y el dimensionado de los FACTS.

Tanto la selección de consigna, como la ubicación y dimensionado de FACTS, son problemas complejos de optimización que involucran múltiples variables con relaciones no-lineales entre sí. Además, estos problemas suelen plantear la consecución de varios objetivos al mismo tiempo, generalmente relacionados con la estabilidad de la tensión y la eficiencia de las redes [10], por lo que pueden ser tratados como problemas de optimización multi-objetivo.

Para resolver estos problemas se han empleado múltiples técnicas distintas. Los métodos de optimización clásicos fueron los primeros en ser utilizados para este propósito debido a su simplicidad. Estos métodos proporcionan resultados relativamente buenos aunque, al no estar diseñados para optimizaciones multi-objetivo, se vuelven complejos a la hora de implementar varias funciones objetivo [10]. Además, en esos casos, el resultado suele estar condicionado por los supuestos en los que se basa la agregación de los distintos objetivos en una única función objetivo.

Recientemente, el desarrollo de técnicas relacionadas con la Inteligencia Artificial (AI, por sus siglas en inglés) ha permitido su uso en la resolución de los problemas de análisis del impacto de dispositivos FACTS en los SEP. Estas técnicas se han popularizado por su eficiencia y buen resultado. A este respecto, dos técnicas han sido particularmente utilizadas. Por un lado, la Optimización por Enjambre de Partículas (PSO, por sus siglas en inglés), y por otro los Algoritmos Genéticos (GA, por sus siglas en inglés) han sido empleados en multitud de estudios de investigación [25]. Adicionalmente, se han propuesto soluciones híbridas, que combinan varias técnicas basadas en AI, o técnicas de AI con métodos tradicionales.

Un método de optimización multi-objetivo alternativo a los anteriores es el método basado en la optimalidad de Pareto. Este método se basa en la selección de un conjunto de soluciones para las que ninguno de los objetivos puede ser mejorado sin perjudicar alguno de los objetivos restantes (soluciones ”no dominadas”). Básicamente, el método de Pareto proporciona un conjunto de soluciones de compromiso entre los diferentes objetivos.

Las funciones objetivo más comunes para evaluar el impacto de los dispositivos FACTS en los sistemas eléctricos son las relativas a la estabilidad de la tensión, seguidas de los costes y las pérdidas en la transmisión eléctrica [9]. Recientemente, se han añadido a estos estudios funciones objetivo relacionadas con el bienestar social y el impacto ambiental [3]. Los índices en los que se basan estas funciones objetivo suelen ser seleccionados mediante procedimientos no sistemáticos, basados en el conocimiento de los investigadores o ingenieros. No obstante, la selección de índices mediante procedimientos sistemáticos puede proporcionar una solución más generalizable y que tenga en cuenta las interacciones entre las distintas variables [49].

Una herramienta interesante para la elección de índices es la selección de atributos. En el ámbito del Machine Learning y la minería de datos, la selección de atributos se usa para elegir el menor conjunto de ellos que proporciona la información más completa sobre un sistema o problema [56]. Un método frecuentemente utilizado para la selección de atributos es la Información Mutua (MI), que se basa en la Teoría de la Información. La MI mide la cantidad de información que una determinada variable, índice o atributo comparte con otra [56]. En este estudio, la MI se ha usado para seleccionar aquellos índices que comparten menos información y, por lo tanto, proporcionan una información más complementaria sobre el problema.

B.3 El problema de la variación de la demanda

Históricamente, el análisis de los sistemas eléctricos se ha realizado a través del cálculo determinista del flujo de carga en determinados escenarios ”extremos”, en base a predicciones de demanda [115]. En la planificación de los sistemas de transmisión, las predicciones a largo plazo se basan en predicciones de variables socio-económicas y su correlación con la evolución histórica de la demanda eléctrica [116]. Como resultado, se establecen uno o varios valores de demanda ”punta” que se usan para representar los ”casos más desfavorables” en la operación de los SEP. Eventualmente se tienen en cuenta también escenarios ”valle”, aquellos con menor potencia demandada. En los últimos años, estos escenarios han sido combinados con distintos escenarios de generación renovable para tener en cuenta su influencia.

La demanda en distintas zonas de los sistemas eléctricos puede comportarse de manera distinta [124], lo que puede afectar a los estudios de planificación. Pueden ocurrir situaciones de riesgo en cuanto a la estabilidad del sistema en condiciones de operación distintas a la ”punta” de demanda. Al mismo tiempo, pueden producirse congestiones, sobrecargas o problemas de voltaje en distintas zonas de los sistemas eléctricos en función de las condiciones de demanda. El ”escenario más desfavorable” puede, por lo tanto, no ser el enfoque apropiado para los problemas de planificación de redes eléctricas a menos que sea aceptable sobredimensionar las redes para asumir esta incertidumbre.

Recientemente, el crecimiento de la penetración de generadores renovables ha aumentado la incertidumbre en la operación y análisis de los sistemas eléctricos. Estos generadores no pueden ser incluidos en el despacho de potencia puesto que no pueden asegurar una cierta cantidad de potencia en un momento concreto en el futuro. La potencia generada por estos equipos suele restarse de la demanda total para computar los que se conoce como *demanda neta* [114]. En este contexto, las interacciones entre la demanda y los generadores renovables deben ser consideradas. Para ello es preciso modelar la demanda de una manera más detallada, pues el enfoque determinista excluye gran cantidad de información sobre el comportamiento real de la demanda [118].

Por estos motivos se hace necesario contar con métodos más detallados para modelar la demanda y la generación renovable para asegurar resultados adecuados en la planificación de los sistemas eléctricos modernos. Estos modelos deberán cumplir con dos requisitos principales: deberán representar el comportamiento real de la variable y deberán permitir modelar el comportamiento futuro de la misma. Los modelos encontrados en la literatura suelen estar basados en alguna de las siguientes técnicas: Simulación Monte Carlo (MCS, por sus siglas en inglés), Perfiles de Carga (LPs, por sus siglas en inglés) y datos históricos.

La técnica MCS permite simular la demanda futura al estar basada en funciones de densidad de probabilidad. Si bien, las herramientas más comunes para generar muestras a partir de las funciones de probabilidad generan muestras independientes [142], lo que hace que estas técnicas no puedan reflejar las coincidencias en los patrones de las distintas variables. Por lo tanto, la representatividad de los escenarios generados a partir de estas técnicas no está asegurada.

Los perfiles de carga sí pueden cumplir con ambos requisitos, respetando las coincidencias entre patrones y generando escenarios que permitan simular la demanda futura. Sin embargo, a pesar de que se han encontrado multitud de trabajos relativos a la extracción de perfiles a partir de datos de demanda, apenas se han encontrado trabajos que permitan generar escenarios de demanda a partir de los mismos [129]. Estos métodos se suelen usar para crear escenarios de demanda agregados, pero pueden permitir modelar la demanda de una manera desagregada.

Los datos históricos proporcionan información detallada de la demanda de los sistemas eléctricos y reflejan las coincidencias entre los patrones de distintas variables, al tratarse de series de datos reales. Sin embargo, estos datos no pueden usarse para representar la demanda futura de una forma fiable [153], y su representatividad se limita al sistema eléctrico en el que fue medida la demanda. Los datos históricos de un sistema eléctrico concreto no pueden usarse para simular la demanda eléctrica de otro, especialmente si la demanda se analiza de manera desagregada.

Por todo esto, no se ha encontrado una técnica que permita modelar satisfactoriamente la demanda como un fenómeno desagregado, respetando las coincidencias entre los patrones de demanda. Queda fuera del objeto de esta investigación desarrollar una técnica para el modelado de la demanda, por lo que se ha empleado una de las técnicas existentes. Se han usado datos históricos de la demanda de distintas subestaciones [125] para poder modelar la demanda de manera distribuida.

B.4 Objetivo e hipótesis de investigación

El objetivo de esta investigación es proponer una metodología de análisis del impacto de los FACTS en los SEP que tenga en cuenta las variaciones tanto de la potencia demandada como de su distribución entre los nodos del sistema. Para ello, se han estudiado y comparado distintos parámetros relacionados con el funcionamiento de la red y se ha desarrollado un método para la selección de los índices en función de la información que aportan sobre el problema. La metodología propuesta ha sido utilizada para la ubicación de un dispositivo FACTS y para la selección del valor de referencia de su control de tensión usando datos distribuidos.

El impacto de los dispositivos FACTS en los sistemas eléctricos ha sido analizado por múltiples autores usando distintas técnicas de optimización y funciones objetivo. Sin embargo, sólo una pequeña parte de ellos incluye los efectos de las variaciones de la demanda en su análisis. De hecho, la mayoría de los estudios de investigación centra su evaluación en uno, o unos pocos, escenarios de demanda [10]. De modo similar, los estudios realizados por los TSOs suelen usar el enfoque ”punta/valle”, que adolece de las mismas limitaciones. Dadas las transformaciones que vienen sufriendo los sistemas eléctricos, se hace necesario desarrollar herramientas de análisis del impacto de los dispositivos FACTS en los SEP que incluyan las variaciones de la demanda. En concreto, las variaciones de la potencia demandada y su distribución deben ser tenidas en cuenta en estos análisis.

El impacto de los FACTS en los sistemas eléctricos depende de múltiples variables. En particular, se ha demostrado que la interacción entre la generación renovable no gestionable y las variaciones de la demanda pueden afectar de manera significativa a los resultados de estos estudios [26]. Los autores han demostrado que, en presencia de generadores renovables, el escenario ”punta” puede no ser el escenario adecuado para el análisis, ya que no asegura un resultado óptimo. En consecuencia, el número y la configuración de los escenarios de demanda se vuelven cruciales para asegurar un resultado robusto en estos análisis.

Es importante resaltar que las variaciones de la demanda, especialmente las relacionadas con su distribución entre los nodos o subestaciones del sistema, puedan afectar a los resultados de los estudios de evaluación del impacto de los FACTS. En esta investigación, se propone una metodología para el análisis del impacto de los dispositivos FACTS que tenga en cuenta dichas variaciones de la demanda. Esta metodología se ha aplicado a la ubicación de FACTS, usando datos de demanda históricos distribuidos, bajo la siguiente hipótesis:

- **Hipótesis 1:** considerar un mayor número de escenarios de demanda con distribución variable entre los nodos proporciona mejores resultados en los estudios de ubicación de dispositivos FACTS.

Por otra parte, es importante resaltar la influencia intrínsecamente zonal del control de tensión. Del mismo modo que esto hace que los dispositivos FACTS deban ser adecuadamente ubicados, esta característica hace que deba prestarse especial atención a su configuración. Este aspecto, sin embargo no ha sido suficientemente estudiado, de acuerdo con la revisión bibliográfica realizada.

Como parte del análisis del impacto de los dispositivos FACTS en los sistemas eléctricos, la selección de su referencia de control de tensión puede verse influenciada por múltiples variables. En particular, las variaciones de la demanda pueden tener una influencia significativa en los resultados de estos estudios. Por eso, se ha considerado importante tener en cuenta un número suficiente de escenarios de demanda que permitan representar adecuadamente su comportamiento.

En esta investigación, se ha aplicado la metodología propuesta a la búsqueda de un valor de referencia adecuado para el control de la tensión mediante dispositivos FACTS. Se han usado datos de demanda históricos distribuidos con el objetivo de incluir las variaciones de demanda en el análisis. Este enfoque se basa en las siguientes hipótesis:

- **Hipótesis 2:** el valor de referencia influye en la eficacia del control de tensión mediante dispositivos FACTS.

- **Hipótesis 3:** considerar un mayor número de escenarios de demanda con distribución variable entre los nodos proporciona mejores resultados en los estudios de configuración de dispositivos FACTS.

B.5 Propuesta metodológica

En esta investigación, el problema del análisis del impacto de los dispositivos FACTS en los sistemas eléctricos se ha planteado como una optimización multi-objetivo basada en índices que miden el comportamiento del sistema. Estos índices se basan, a su vez, en variables medidas a partir del cálculo del Flujo de Carga (PF, por sus siglas en inglés). Se han evaluado los distintos índices en función de la información estadística que proporcionan. Aquellos que aportan una información más complementaria entre sí han sido seleccionados para el análisis del impacto de los dispositivos FACTS en los sistemas eléctricos. Se ha propuesto una metodología, basada en el concepto de optimalidad de Pareto, con el objetivo de mejorar las herramientas para la toma de decisión relativa a la planificación de las redes de transmisión.

De la revisión bibliográfica se extrae que no existen métodos viables para representar adecuadamente la demanda como un fenómeno desagregado. Por eso se han tomado datos históricos distribuidos para crear escenarios de demanda horarios que representen un año de operación del sistema eléctrico. En base a los datos del sistema de prueba IEEE de 14 nodos, se han asignado valores de demanda a cada una de las cargas para crear 8760 escenarios de operación. Para cada escenario, se actualizaron los valores de demanda de cada nodo y se realizó un optimización del flujo de carga (OPF, por sus siglas en inglés). A continuación, se realizó un análisis P-V para el *caso base* (aquel en el que no se ha implementado el dispositivo FACTS) y se almacenaron los valores tomados por las distintas variables. Para cada posible solución, se implementó el dispositivo FACTS con la configuración adecuada, y se realizó de nuevo un OPF y un análisis P-V para integrar cada solución y evaluar el margen de carga, así como el resto de las variables del sistema, para cada una de ellas. En la figura B.1 se puede observar el diagrama de flujo de este proceso de simulación.

Una vez se realizaron las simulaciones, se calcularon distintos índices para evaluar el impacto del dispositivo FACTS en función de las variables del sistema. Estos índices fueron elegidos para reflejar distintos aspectos de la operación de sistemas eléctricos tanto desde un punto de vista técnico como económico. De la revisión bibliográfica se pudo determinar que los índices de estabilidad de la tensión son los más frecuentemente usados, seguidos de las pérdidas de transmisión [9], mientras que las emisiones de gases de efecto invernadero han sido añadidas recientemente para tener en cuenta el impacto ambiental de la operación de los sistemas eléctricos en los estudios de planificación [108].

En esta investigación se han seleccionado 6 índices para evaluar el impacto de los dispositivos FACTS en los sistemas eléctricos. Por un lado, se han elegido dos índices de estabilidad de la tensión: el margen de carga, las pérdidas de reactiva y la desviación de la tensión. Por otro lado, se han incluido dos índices para reflejar la eficiencia de los SEP; en concreto, los costes de operación y las pérdidas de potencia activa. Por último, se incluyeron las emisiones de gases de efecto invernadero para evaluar la influencia del control de tensión usando dispositivos FACTS en el impacto ambiental de los sistemas eléctricos.

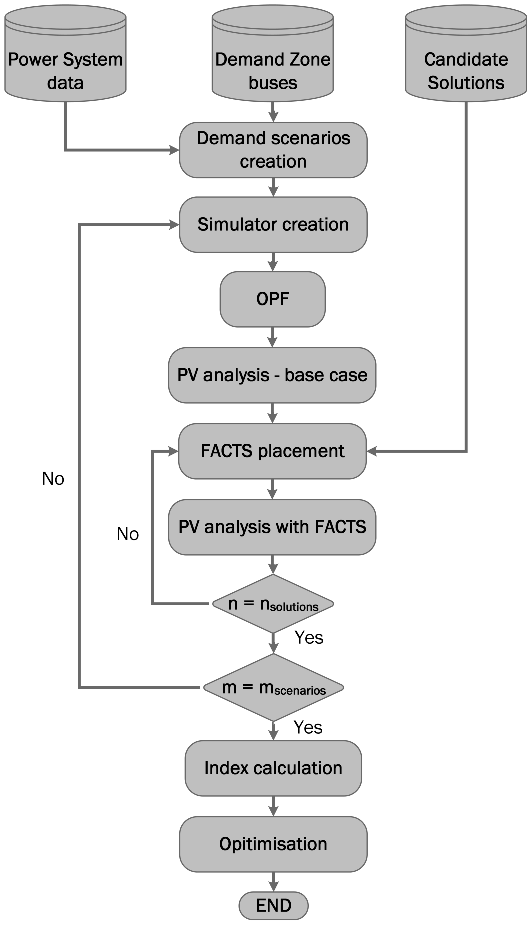

Figure B.1: Diagrama de flujo del proceso de simulación.

Dado el gran número de simulaciones realizadas para analizar las distintas ubicaciones en todos los escenarios de demanda, se han generado una enorme cantidad de valores para cada índice, ya que estos reflejan un atributo de una situación de operación concreta. Por ese motivo, se ha propuesto una medida única que refleje el comportamiento medio del sistema para cada uno de los índices. Esta medida se ha calculado como la "mejora relativa" provocada por el dispositivo FACTS con respecto al "caso base". Para tener en cuenta todos los escenarios de demanda, se ha calculado la media de esta medida normalizada para todos los escenarios. De esta manera se obtiene la Mejora Relativa Media (MRI, por sus siglas en inglés). Esta medida ha sido diseñada para permitir su maximización a través de la optimalidad de Pareto, y se calcula como sigue:

$$MRI_i = \frac{1}{n}\sum_{j=1}^{n}\frac{PI^{i,j}_{FACTS} - PI^{j}_{base}}{PI^{j}_{base}} \tag{B.1}$$

Donde PI^{j}_{base} es el valor del índice de evaluación en el caso base (sin dispositivo FACTS) para el $j-esimo$ escenario de demanda y PI^{j}_{base} es el valor del índice para el mismo escenario de demanda cuando el dispositivo se ha implementado de acuerdo con la $i-esima$ solución en estudio.

Sin embargo, la mayoría de los índices seleccionados deben ser minimizados (a excepción de λ). Puesto que el MRI debe ser maximizado, se ha optado por cambiar el signo del MRI referido a dichos índices antes de ser minimizados. El MRI para dichos índices se calcula como sigue:

$$MRI_i = -\frac{1}{n}\sum_{j=1}^{n}\frac{PI_{FACTS}^{i,j} - PI_{base}^{j}}{PI_{base}^{j}} = \frac{1}{n}\sum_{j=1}^{n}\frac{PI_{base}^{j} - PI_{FACTS}^{i,j}}{PI_{base}^{j}} \tag{B.2}$$

Los índices utilizados en la planificación de los sistemas eléctricos, y particularmente en la ubicación de dispositivos FACTS, no suelen seleccionarse mediante procedimientos sistemáticos. Por el contrario, la selección de índices suele basarse en el conocimiento y la experiencia de los ingenieros o investigadores. En este trabajo, se ha utilizado la selección de atributos basada en la Información Mutua para la selección de índices dentro de la metodología para la evaluación del impacto de los dispositivos FACTS. En este contexto, la información que aporta cada uno de los índices se vuelve relevante, y aquellos que aporten una información más heterogénea deben ser incluidos en el estudio. La Información Mutua (MI, por sus siglas en inglés), puede utilizarse como un método de selección de índices generalizable que permite establecer un criterio claro. El algoritmo de selección de índices desarrollado permite seleccionar el subconjunto de índices con menor MI entre sí, por lo que aportan una información más complementaria.

El cálculo de la MI para la selección de índices puede provocar problemas de computación debido al aumento exponencial de la carga computacional. Sin embargo, en este caso, el número de combinaciones es abordable, y al calcular la MI para todas las combinaciones de dos índices es posible encontrar una mejor solución, ya que se puede tener en cuenta las interdependencias entre ellos.

El algoritmo desarrollado permite descartar aquellos índices que comparten más información a partir de la métrica D, basada en la MI, y que se calcula como sigue:

$$D(X,Y) = 1 - \frac{I(X;Y)}{H(X,Y)} \tag{B.3}$$

Donde $I(X;Y)$ es la Información Mutua entre dos variables X e Y y $H(X,Y)$ es la entropía conjunta de ambas variables.

Esta métrica se ha calculado para todas las combinaciones de dos índices y para cada una de las soluciones candidatas. Sin embargo, se necesita una única medida de la interdependencia entre los índices, por lo que se ha seleccionado el menor valor de la distancia D para cada combinación de índices de entre los valores relativos a las distintas soluciones estudiadas. De este modo, cada pareja de índices quedó representada por la mínima distancia (mayor interdependencia) entre sí. Una vez computadas las distancias, se usó un procedimiento de eliminación secuencial para obtener el subconjunto de índices que aportan una información más complementaria al análisis. Este procedimiento se describe a continuación:

1. Computar las distancias agregadas: se suman las distancias entre cada índice con el resto para evaluar si interdependencia con el conjunto.

2. Seleccionar los pares de índices ”nominados”: la pareja de índices con una menor distancia D entre sí son seleccionados como candidatos a ser excluidos del conjunto.

3. Eliminar un índice del conjunto: de entre los índices nominados, aquel con menor distancia agregada es eliminado.

4. Repetir pasos 2 y 3 hasta que el tamaño del subconjunto restante coincida con el tamaño deseado.

Por último, se ha propuesto un método para la toma de decisiones basado en la optimalidad de Pareto. Un problema de optimización multi-objetivo puede ser planteado tal que:

$$maximizar \quad F(x) = (f_1(x), ..., f_m(x)); \quad Sujeto\, a \quad x \in \Omega \tag{B.4}$$

Donde f_i $(i = 1, m)$ es el conjunto formado por m funciones objetivo en función de la variable de decisión x, dentro del espacio de decisión Ω.

Si asumimos dos vectores tal que $u = (u_1, ...u_m), v = (v_1, ...v_m) \in R^m$, siendo R^m el ”espacio objetivo”, puede decirse que u domina a v si $u_i \geq v_i$ para cada $i = 1, ...m$ y $u \geq v$. Según el concepto de optimalidad de Pareto, una solución $x^* \in \Omega$ es óptima si no existe $x \in \Omega$ tal que $F(x)$ domine $F(x^*)$. En otras palabras, una solución es Pareto-óptima si ninguno de los objetivos puede ser mejorado sin empeorar alguno de los restantes [161].

En base a los índices seleccionados y a los resultados del proceso de simulación, las soluciones propuestas fueron evaluadas usando este método. Si dos o más soluciones resultan ser seleccionadas, el método de selección de índices servirá para elegir un tercer índice según el cual se ordenarán las soluciones Pareto-óptimas. La solución óptima sería aquella solución Pareto-óptima que maximice la MRI del tercer índice tal que:

$$Maximizar \quad MRI_j^i; \quad Sujeto\, a \quad i \in \imath \tag{B.5}$$

Donde j denota el índice al que se refiere la MRI e i denota una solución Pareto-óptima concreta dentro del conjunto de $\imath$ soluciones Pareto-óptimas.

B.6 Trabajo Experimental

En esta sección se describe el trabajo experimental realizado en esta investigación. En ella se ha desarrollado una demostración teórica de la influencia de la distribución de la demanda en la ubicación óptima de la compensación de reactiva. Además, se ha probado la eficacia de la metodología descrita para la ubicación de un dispositivo FACTS (STATCOM) y su configuración.

B.6.1 Efecto de la distribución de la demanda en la ubicación de dispositivos FACTS

Como se ha podido demostrar teóricamente, la distribución de la demanda condiciona los resultados de la ubicación de dispositivos FACTS. Si bien, era necesario obtener una comprobación empírica para validar esta conclusión. Además, es interesante entender la influencia de esta variable en la ubicación de estos dispositivos. Con este objetivo se diseñó un experimento que incluye todas las combinaciones viables de la distribución de demanda entre 3 zonas de demanda para un valor fijo de demanda agregada. Estas zonas de demanda estan formadas por los nodos 2 y 3 en el caso de la zona 1, por los nodos 4, 9, 10, 11 y 14 en el caso de la zona 2 y por los nodos 5, 6, 12 y 13 en el caso de la zona 3. Este experimento permitió comprobar la influencia de la distribución de la demanda en los procedimientos de ubicación de dispositivos FACTS. Es importante mencionar que este experimento fue publicado como un artículo en una revista científica indexada [165].

En las figuras B.2 y B.3 pueden observarse los resultados usando como función objetivo el *Fused Performance Index* (FPI) y el márgen de carga (λ) respectivamente. La base de estas figuras es el procedimiento de representación desarrollado en[166]. Este procedimiento permite representar datos tridimensionales en un plano a través de un triángulo. En nuestro caso, este triángulo está formado por todos los escenarios de distribución de demanda, siendo sus vértices aquellas distribuciones en las que la totalidad de la demanda se encuentra en cada una de las zonas de demanda. El centroide de dicho triángulo es el punto en el que la demanda se encuentra igualmente distribuida entre las tres zonas de demanda. La presencia de espacios vacíos en el triángulo refleja la existencia de escenarios de distribución de demanda para los que no se pudo calcular el flujo de carga.

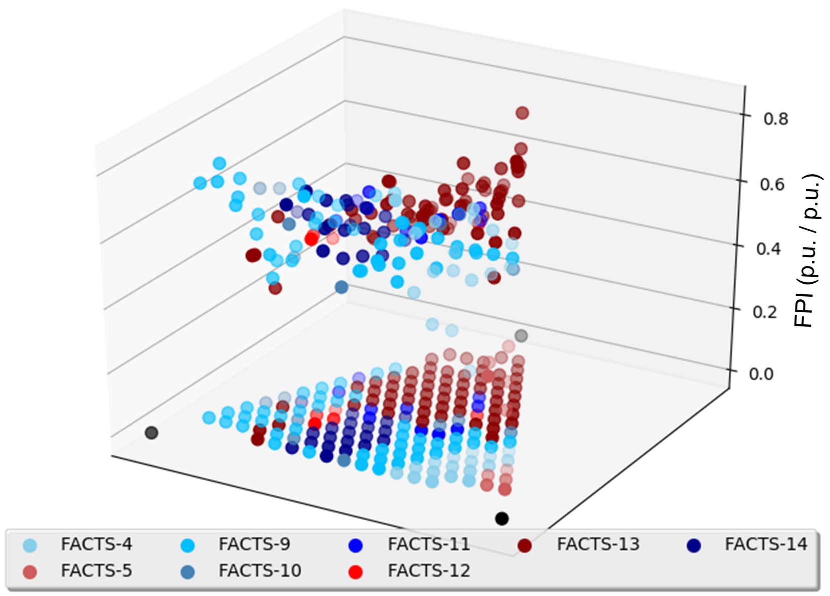

Figure B.2: Mejores ubicaciones frente a valores de FPI según escenarios de demanda.

Este experimento ha permitido comprobar que la distribución de la demanda tiene un efecto relevante en la ubicación de dispostivos FACTS. Los resultados parecen demostrar una doble correlación. Por un lado los nodos más frecuentemente seleccionados coinciden con los nodos más débiles. Por otro lado, los nodos seleccionados suelen encontrarse en las zonas de mayor demanda o en sus nodos cercanos.

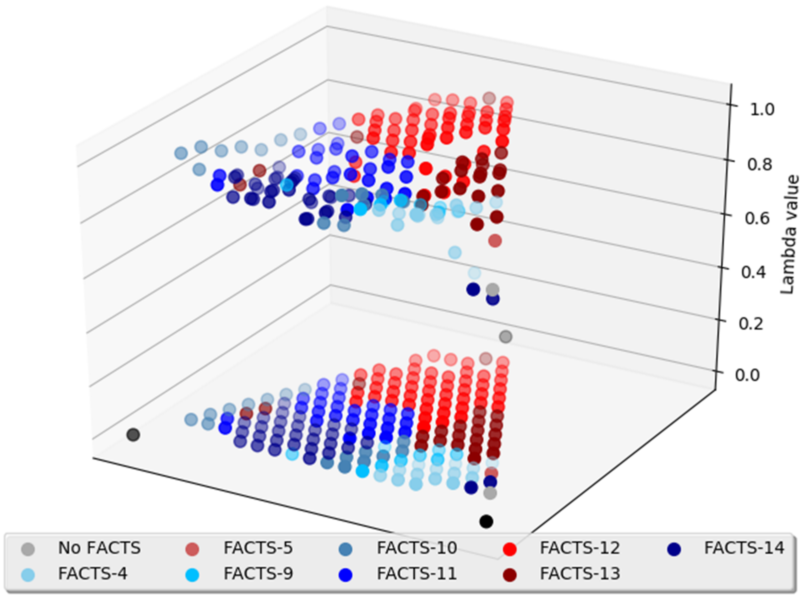

Figure B.3: Mejores ubicaciones frente a valores de λ según escenarios de demanda.

Se ha podido demostrar que distintas funciones objetivo proporcionan resultados distintos. Usando el FPI, el nodo más frecuentemente seleccionado es el nodo 12, aunque en este caso los resultados varían sensiblemente con los cambios en la distribución de la demanda. Usando λ como función objetivo, el nodo que más veces es seleccionado es el nodo 9, y los resultados son menos sensibles a las variaciones de la distribución de la demanda.

B.6.2 Ubicación de dispositivos FACTS usando datos distribuidos

Se realizó un experimento para validar la metodología propuesta como solución a la ubicación de dispositivos FACTS teniendo en cuenta las variaciones de la demanda. Para ello se crearon 8760 escenarios de demanda y se realizaron simulaciones con diferentes ubicaciones del STATCOM. Posteriormente se seleccionaron los índices que aportan una mayor información al problema y se utilizó el procedimiento de toma de decisión para elegir la mejor ubicación en base a los índices más relevantes. Los índices fueron filtrados antes del cálculo de la distancia D para excluir aquellos que fueran irrelevantes. Los índices con una mejora relativa media (MRI, por sus siglas en inglés) tal que $\overline{MRI} \leq 0.005$ y $\sigma_{MRI} \leq 0.025$ fueron excluidos. Los valores de distancia para el resto de índices se muestran en la tabla B.1. Aplicando el procedimiento de selección de índices se escogieron el margen de carga (λ) y las desviaciones para la tensión como índices de evaluación del comportamiento del sistema.

	λ	**Volt. Dev.**	**Q Loss**	**P Loss**
λ	0	0.8323	0.8436	0.8496
Volt. Dev.	-	0	0.6787	0.7295
Q Loss	-	-	0	0.3478
P Loss	-	-	-	0

Table B.1: Distancia D entre los índices relevantes dentro del conjunto original.

Se realizaron distintas pruebas para demostrar la necesidad de considerar un mayor número de escenarios de demanda con distribución variable entre los nodos en estos estudios. Se crearon cuatro sub-conjuntos de escenarios de demanda separándolos en cuartiles en función de su distribución de demanda, desde escenarios con una distribución de la demanda más uniforme, hasta escenarios con una distribución muy desigual. En la figura B.4 se pueden encontrar los resultados de esta metodología para la ubicación de dispositivos FACTS para los distintos sub-conjuntos de escenarios y para el conjunto de escenarios anual. Los resultados se muestran en función de la mejora relativa media de las desviaciones de la tensión y el margen de carga.

Los resultados muestran que se pueden establecer tres grupos de soluciones. En primer lugar, los nodos 4, 5, 11 y 12 presentan una mejora relativamente pequeña en ambos índices. En segundo lugar, el nodo 14 muestra buenos resultados en cuanto al margen de carga, pero es la peor opción teniendo en cuenta las desviaciones de la tensión. Finalmente, los nodos 9, 10 y 13 presentan buenos resultados en ambos índices. Los resultados se mostraron sensibles a las variaciones en la distribución de la demanda, aunque la solución Pareto-óptima resultó ser el nodo 9 en todos los casos.

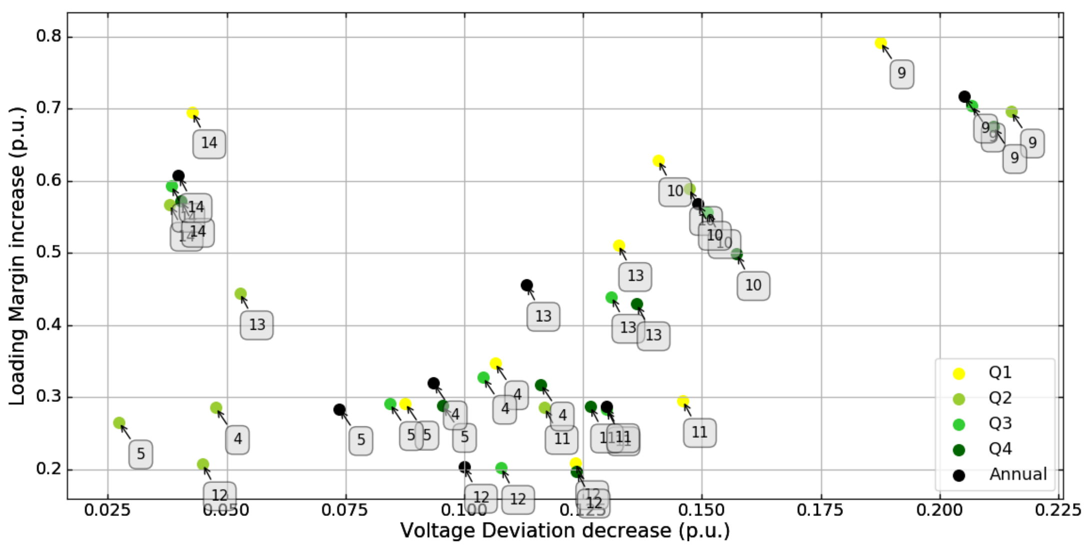

Figure B.4: Ubicación de dispostifivos FACTS. Desviación de la tensión frente a λ en función de la distribución de la demanda. Comparación con los valores medios anuales para escenarios de demanda con distribución variable.

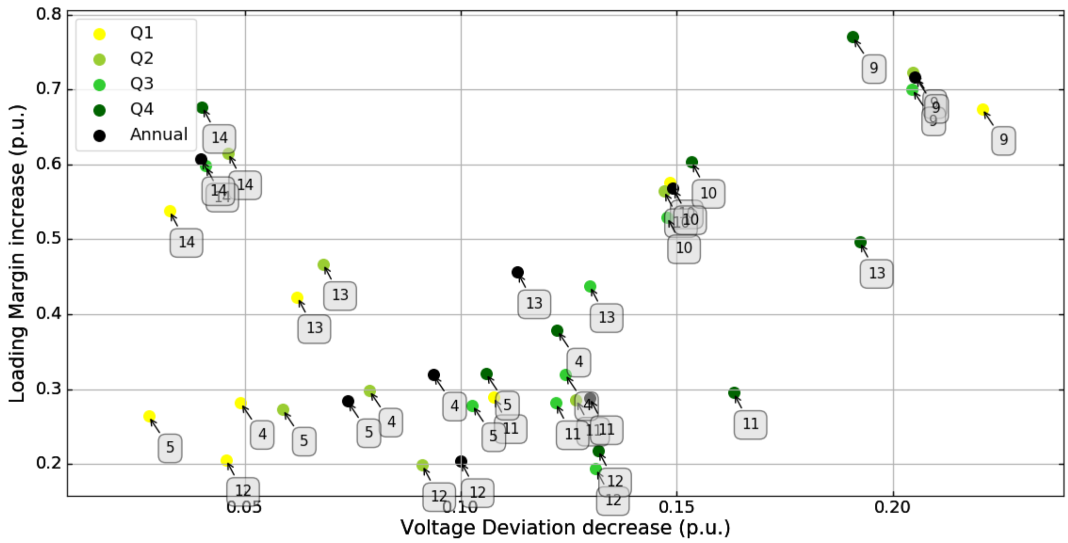

Figure B.5: Ubicación de dispostifivos FACTS. Desviación de la tensión frente a λ en función de la potencia total de los escenarios de demanda. Comparación con los valores medios anuales para escenarios de demanda con distribución variable.

Del mismo modo, se crearon cuatro sub-conjuntos de escenarios de demanda en función de cuartiles en base a la potencia total de cada escenario; desde escenarios con poca demanda hasta escenarios con una alta demanda de potencia. Los resultados muestran de nuevo variaciones en los valores de los índices que, en algunos casos, como el del nodo 13, son significativas. No obstante, la solución óptima es el nodo 9 en todos los caso (ver figura B.5).

Se ha realizado una comparativa entre la metodología propuesta y el enfoque basado en el caso más desfavorable . Para ello, se han analizado los escenarios punta y valle, pero también aquellos escenarios que presentan un mayor y menor margen de carga en el sistema sin la presencia del dispositivo FACTS. Los resultados muestran diferencias sustanciales entre ambos enfoques. Además, se ha demostrado que, usando escenarios de demanda con una distribución de la demanda variable, el escenario punta no se corresponde con el escenario con menor margen de carga (ver tabla B.6.2). En otras palabras, si se tiene en cuenta una distribución variable de la demanda, el escenario punta podría no ser el escenario más desfavorable para la evaluación del impacto de los dispositivos FACTS.

	Punta	**Valle**	**min λ**	**max λ**
Distribución de demanda constante	906	4275	906	4275
Distribución de demanda variable	906	4275	762	4275

Table B.2: Escenarios de demanda correspondientes a los escenarios punta, valle, mínimo λ y máximo λ.

B.6.3 Configuración del control de los dispositivos FACTS usando datos distribuidos

Por último, se ha diseñado un experimento similar al anterior para validar la metodología propuesta a la hora de seleccionar un valor de referencia para el control de tensión del STATCOM. Utilizando el mismo procedimiento, se analizaron distintos valores para determinar cual proporciona una mayor efectividad del control de tensión y analizar la influencia de las variaciones de la demanda en la solución a este problema (ver figuras B.6 y B.7).

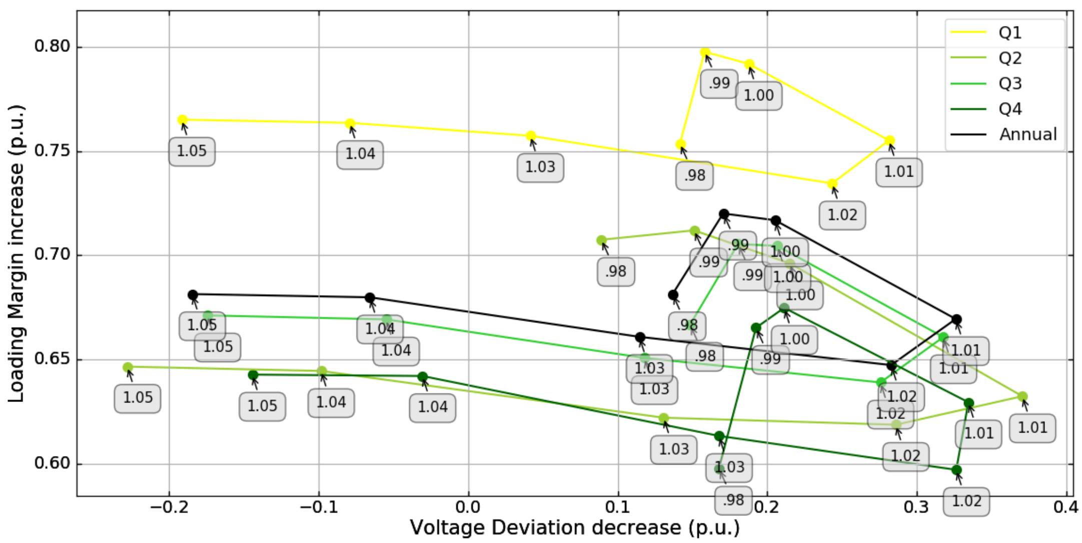

Figure B.6: Configuración de dispostifivos FACTS. Desviación de la tensión frente a λ en función de la distribución de la demanda. Comparación con los valores medios anuales para escenarios de demanda con distribución variable.

Los resultados de aplicar la metodología propuesta a la configuración del STATCOM muestran que, a partir de un valor de referencia de 0.98 p.u., las desviaciones de la tensión disminuyen con el aumento del valor de referencia. Esto es así hasta que se alcanza el valor de referencia de 1.01 p.u., a partir del cual, las desviaciones de tensión aumentan con el aumento del valor de referencia del control de tension. En lo referido al margen de carga, los valores de 0.99 y 1.00 p.u. muestran resultados sensiblemente mejores que el resto. Si bien, los resultados se ven fuertemente influenciados por las variaciones de la distribución de la demanda, pero sobre todo de la potencia total de los escenarios. Las soluciones Pareto-óptimas también varían en función de los escenarios de demanda escogidos, aunque aquellas comprendidas entre 0.99 y 1.01 p.u. resultan serlo con más frecuencia.

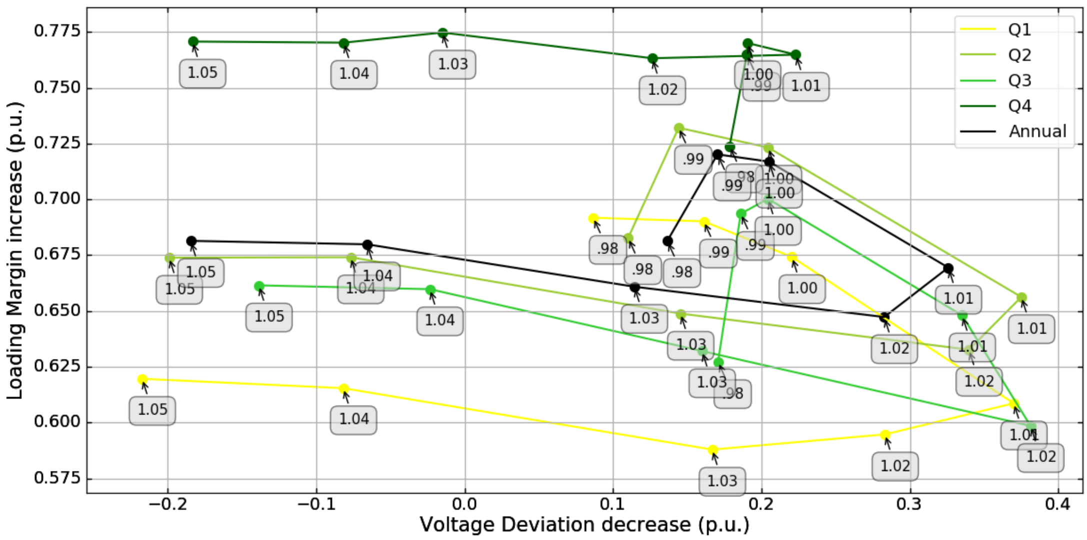

Figure B.7: Configuración de dispostifivos FACTS. Desviación de la tensión frente a λ en función de la potencia total de los escenarios de demanda. Comparación con los valores medios anuales para escenarios de demanda con distribución variable.

B.7 Conclusiones

De la revisión bibliográfica se extrajo información relevante para diseñar las hipótesis de investigación y la solución propuesta. Posteriormente, se llevaron a cabo los experimentos que permitieron validar tanto las hipótesis planteadas como la metodología propuesta. De este trabajo, se obtuvieron conclusiones útiles para la planificación de los sistemas eléctricos modernos. A continuación se describen las ideas principales extraídas de la revisión bibliográfica, para luego presentar las conclusiones obtenidas a partir del trabajo experimental.

La revisión de las técnicas más frecuentes para el análisis del impacto de los FACTS en los sistemas eléctrico permitió conocer algunos aspectos en los que pueden ser mejorados. Se ha encontrado que las técnicas de ubicación de estos dispositivos no suelen considerar un número significativo de escenarios de demanda y generación. Del mismo modo, los procedimientos usados tradicionalmente por los operadores de la red suelen estar basados en el enfoque ”punta/valle”, por lo que se centran en unos pocos escenarios. Como se ha demostrado en [26], la presencia de generadores renovables no gestionables hace que el enfoque ”punta/valle” pueda no proporcionar los mejores resultados. Por tanto, es importante incluir un número suficiente de escenarios para tener en cuenta las interacciones entre los distintos elementos del sistema eléctrico.

En aquellos estudios que incluyen gran cantidad de escenarios de demanda suelen utilizarse alguna de las siguientes técnicas: Simulación Monte Carlo, Perfiles de Carga o datos históricos. Se ha realizado una revisión bibliográfica sobre estas técnicas, prestando especial atención a su capacidad para simular la demanda, presente y futura, como un fenómeno desagregado. Las conclusiones de esta revisión son las siguientes:

- Los métodos basados en la simulación Monte Carlo requieren un conjunto de reglas y restricciones que permitan "guiar" el proceso de generación de muestras para respetar las coincidencias en los perfiles de demanda y/o generación.
- Las técnicas basadas en Perfiles de Carga se basan en datos históricos y no suelen incluir métodos para representar la demanda futura ([153] y [133]). A pesar de que existen numerosos trabajos referidos al cálculo de perfiles de carga, muy pocos han aportado soluciones para la creación de escenarios de demanda a partir de ellos [129]. Por ello, son pocos los estudios sobre perfiles de carga para la creación de escenarios de demanda desagregados y éstos tienen una representatividad limitada.
- Los datos históricos proporcionan información detallada sobre la demanda en los sistemas eléctricos. Estos datos representan adecuadamente las interacciones entre las distintas variables, pero pueden no representar adecuadamente situaciones futuras [153]. La representatividad de los escenarios de demanda basados en datos históricos está asegurada sólo para el sistema eléctrico del cual fueron medidos, especialmente si se estudia la demanda de forma desagregada.

Para validar las hipótesis de investigación y evaluar la metodología propuesta, se han realizado tres experimentos diferentes. Las conclusiones principales de estos experimentos se presentan a continuación.

B.7.1 Efecto de la distribución de la demanda en la ubicación de dispositivos FACTS

De este estudio se extrae que debe tenerse en consideración la distribución de la demanda para asegurar unos resultados robustos en la ubicación de dispositivos FACTS. Además, se ha comprobado la influencia de la función objetivo sobre los resultados de este procedimiento.

La conclusión principal alcanzada tras este experimento es que la distribución de la demanda tiene una influencia relevante en la ubicación de dispositivos FACTS. Se han encontrado similitudes y discrepancias en los resultados obtenidos usando distintas funciones objetivo: λ y el FPI. El primero da como solución el nodo número 12, mientras que el segundo da como mejor resultado el nodo 13. Si bien, independientemente de la función objetivo empleada, se ha demostrado que:

a. los nodos más débiles del sistema son seleccionados frecuentemente para la ubicación del dispositivo.

b. los nodos más frecuentemente seleccionados estaban dentro, o en las proximidades, de las zonas con mayor demanda.

Puesto que este procedimiento está basado en variables de los sistemas eléctricos, estos descubrimientos pueden generalizarse a otros sistemas eléctricos y servir de ayuda para investigadores y planificadores de sistemas de transmisión, a la hora de abordar la ubicación de los dispositivos FACTS. La influencia demostrada de la distribución de la demanda en la solución de estos problemas profundiza en la idea de que un único escenario puede no representar adecuadamente la casuística de estos problemas. El escenario ”punta” podría no ser la mejor opción para evaluar estos problemas, como se ha expuesto en [26].

B.7.2 Ubicación de dispositivos FACTS usando datos distribuidos

La metodología para el análisis del impacto de los dispositivos FACTS en los sistemas eléctricos fue usada en este experimento para la ubicación de un STATCOM en un sistema eléctrico de prueba. El método de selección de índices incluido en esta metodología mostró resultados que son coherentes con la literatura existente. Las desviaciones de la tensión y el margen de carga fueron seleccionados como los índices que aportan mayor información al análisis.

La metodología de análisis del impacto de los dispositivos FACTS, aplicada a la ubicación de un STATCOM, dio como resultado que el bus 9 es la mejor solución. Este resultado es coherente con estudios previos que demuestran que el nodo 9 es la mejor ubicación cuando se estudia el desempeño de los compensadores, en vez de buscar el nodo más débil como ubicación óptima ([101] y [21]).

Se usaron distintos conjuntos de escenarios de la demanda para estudiar la sensibilidad de los resultados a las variaciones en la distribución de la misma. El procedimiento de ubicación se ejecutó para conjuntos de escenarios con distintas características, desde escenarios con una distribución muy homogénea, hasta escenarios con una distribución muy desigual. El nodo 9 demostró ser la mejor solución independientemente de la distribución de la demanda. Por lo tanto, se puede concluir que, a pesar de las variaciones en las funciones objetivo, la decisión sobre la ubicación de FACTS es robusta respecto a la variación de la distribución de la demanda.

Para estudiar más en detalle las implicaciones de las variaciones de la distribución de la demanda, se crearon dos conjuntos de escenarios partiendo de los mismos datos históricos. En el primero, la distribución de la demanda se determina partiendo de la distribución original de cada escenario en los datos históricos. En el segundo conjunto se usó una distribución constante. Estos conjuntos de escenarios fueron usados en las pruebas posteriores, donde se especifican los distintos escenarios: distribución variable o constante.

También se estudió la influencia de la potencia total de los escenarios sobre los resultados del procedimiento. Se organizaron conjuntos de escenarios en función de su potencia total, desde escenarios con menor potencia hasta escenarios con mayor potencia demandada. Los resultados de la ubicación de dispositivos FACTS han demostrado ser sensibles a esta organización. Si bien, unas soluciones (ubicaciones) muestran mayor variabilidad que otras frente a los cambios en la potencia total de los escenarios. Se ha comprobado que la toma de decisión es sensible a los cambios en la potencia del escenario, ya que la forma y composición del frente de Pareto pueden cambiar para escenarios con mayor potencia demandada. Se han comparado los resultados obtenidos en base a escenarios con distribución de demanda constante con los obtenidos con una distribución variable. Los resultados muestran pequeñas diferencias que no son significativas.

Los resultados medios anuales se han comparado con los resultados del ”caso más desfavorable”. Para ello se ha llevado a cabo la búsqueda de la mejor ubicación para el dispositivo FACTS en los escenarios de mayor y menor demanda (punta y valle), y en los de mayor y menor margen de carga (λ). Los resultados demuestran que, cuando se usa una distribución de demanda variable en los escenarios, el escenario ”punta” no coincide con el escenario de mínimo margen de carga. Por lo tanto, el escenario ”punta” podría no ser el verdadero caso más desfavorable, y el uso de una distribución constante de la demanda podría no reflejarlo. Se pudieron observar diferencias sustanciales entre el enfoque propuesto y el enfoque basado en un único escenario, tanto en lo referido al valor de los índices como en cuanto a la decisión final.

Finalmente, se estudiaron distintos métodos para seleccionar conjuntos reducidos de escenarios de demanda. Por un lado se seleccionaron escenarios ”por lotes”, eligiendo aleatoriamente semanas completas de entre los datos anuales. Por otro lado, se seleccionó individual y aleatoriamente el mismo número de escenarios. Los resultados mostraron que pueden crearse conjuntos reducidos de escenarios de demanda sin afectar significativamente al resultado del procedimiento de ubicación de dispositivos FACTS. Los escenarios elegidos individualmente mostraron mejores resultados que los elegidos por semanas, sobre todo para muestras pequeñas. Puesto que los escenarios fueron creados a partir de datos históricos desagregados, estos respetan las coincidencias en los patrones de demanda y generación. Por lo tanto, pueden obtenerse buenos resultados con un número sensiblemente menor de muestras. Se ha comprobado que con 1680 escenarios (10 semanas) los resultados son muy similares a los anuales.

Los resultados muestran que la sensibilidad de la ubicación de dispositivos FACTS a la potencia demandada y su distribución debe ser tenida en cuenta. Los escenarios de demanda deben incluir una distribución de la demanda variable para asegurar unos resultados fiables, especialmente si se usa el enfoque ”punta/valle”. Por lo tanto, este experimento ha permitido validar la primera hipótesis de investigación, que establece que:

- **Hipótesis 1:** considerar un mayor número de escenarios de demanda, con distribución variable entre los nodos, en los estudios de ubicación de dispositivos FACTS proporciona mejores resultados.

Se ha podido comprobar que la metodología propuesta recoge las variaciones de la demanda para que sean tenidas en cuenta en el proceso de ubicación de dispositivos FACTS.

B.7.3 Configuración del control de dispositivos FACTS usando datos distribuidos

La metodología para el análisis del impacto de los dispositivos FACTS en los sistemas eléctricos fue usada en este experimento para evaluar los distintos valores de referencia. Se ha podido observar que los valores medios anuales del aumento del margen de carga tienen un comportamiento altamente no lineal, mostrando valores especialmente altos para ciertos valores de referencia (0.99 y 1.00 p.u.). El índice que mide la reducción de la desviación de la tensión muestra valores negativos para valores de referencia por encima de 1,03 p.u.. Esto quiere decir que el perfil de tensiones empeora a partir de dicho valor de referencia. Se puede observar un punto de inflexión en la tendencia de los resultados al aumentar la referencia del control de tensión. Hasta un valor de referencia de 1.01 p.u., los aumentos en el valor de referencia provocan una reducción de las desviaciones de tensión. A partir de este valor, los aumentos en el valor de referencia generan mayores desviaciones de la tensión. El conjunto de valores Pareto-óptimos para referencia del control se reduce a los valores comprendidos en el intervalo entre 0.99 y 1.01 p.u..

Se ha encontrado una relación directa entre la potencia total de los escenarios utilizados y el aumento del margen de carga ocasionado por el dispositivo FACTS, independientemente de los valores de referencia. También se ha observado que, para valores de referencia altos, la reducción de las desviaciones de tensión tiende a aumentar cuando la potencia total de los escenarios aumenta. Por el contrario, para valores de referencia más pequeños, la reducción de las desviaciones de tensión parece ser inversamente proporcionales a la potencia total de los escenarios. Los resultados muestran que el incremento en el margen de carga es mayor cuanto mayor es la potencia total de los escenarios independientemente del valor de referencia, lo que también sucede con las disminuciones de las desviaciones de tensión, aunque de manera más atenuada. Se ha podido comprobar que el conjunto de soluciones Pareto-óptimas cambia en función del cuartil estudiado, por lo que la decisión sobre el valor de la referencia del control de tensión parece ser sensible a la potencia total de los escenarios de demanda.

También se ha observado que el aumento del margen de carga en el escenario ”punta” se aproxima al valor de 1.00 p.u., mientras que para caso más desfavorable, entendido como el escenario con menor margen de carga inicial, este alcanza el valor de 2.5 p.u.. En ambos escenarios, la influencia de los valores de referencia del control sobre el aumento del margen de carga es despreciable. Respecto de la reducción de las desviaciones de tensión, en ambos escenarios las soluciones entre 0.98 y 1.00 p.u. muestran los mejores resultados. Los resultados medios anuales muestran similitudes con el escenario valle. Ambos muestran mayor variación de los resultados en función los distintos valores de referencia y un conjunto de Pareto formado por los valores 0.99, 1.00 y 1.01 p.u..

La metodología propuesta ha mostrado buenos resultados para la selección del valor de referencia del control de tensión. Los valores con mejor valoración son aquellos próximos a

1.00 p.u., por lo que los resultados coinciden con los esperados. Además, esta metodología ha podido capturar la sensibilidad de los resultados a las variaciones en potencia total de los escenarios de demanda y la distribución de la misma. Las implicaciones de estas sensibilidades deben ser consideradas a la hora de seleccionar la referencia del control de tensión de los dispositivos FACTS.

Por todo ello, se puede considerar que este experimento permitió validar las hipótesis de investigación relativas al control de los dispositivos FACTS. Estas fueron las siguientes:

- **Hipótesis 2:** el valor de referencia influye en la eficacia del control de tensión mediante dispositivos FACTS.

- **Hipótesis 3:** considerar un mayor número de escenarios de demanda, con distribución variable entre los nodos, en los estudios de configuración de dispositivos FACTS proporciona mejores resultados.

B.8 Contribuciones principales

La revisión de la literatura y el trabajo experimental han permitido realizar algunas contribuciones en relación con la problemática de la evaluación del impacto de los dispositivos FACTS en los sistemas eléctricos. En esta sección se presentan las principales contribuciones científicas de esta investigación.

- En el capítulo 2, se ha estudiado la problemática relacionada con el análisis del impacto de los dispositivos FACTS en los sistemas eléctricos. Tras una revisión de los principales métodos y enfoques, se pudo comprobar que el uso un número de escenarios relevante es infrecuente. Algunas investigaciones han demostrado que el nodo más débil en cuanto a estabilidad de la tensión puede no ser la mejor opción para la ubicación de estos dispositivos. También se ha cuestionado el uso del escenario "punta" como base del análisis, pues puede no asegurar los mejores resultados.

- En el capítulo 3, se han analizado los principales métodos para el modelado de la demanda en estudios de planificación de la expansión de los sistemas de transmisión y se ha proporcionado un acercamiento al modelado de la demanda como un fenómeno desagregado. También se han descrito algunos requerimientos del análisis de sistemas eléctricos modernos y se ha encontrado la necesidad de disponer de técnicas de modelado de la demanda mejoradas. Se ha comprobado que existen pocos conjuntos de datos de demanda desagregados y que los métodos para generar escenarios de demanda desagregados son muy infrecuentes. Una parte de las ideas descritas en este capítulo fueron publicadas en el paper *"Power system planning supported by Big Data"*, presentado en la conferencia European Simulation and Modelling, en 2018 [119].

- En el capítulo 4, se proporciona una justificación teórica de la influencia de la distribución de la demanda en la ubicación de dispositivos FACTS en sistemas elécticos. En base a las ecuaciones que describen la transmisión de potencia en los sistemas eléctricos, se desarrolló un modelo reducido que permitiera determinar la influencia de la distribución de la demanda en la ubicación de la compensación de reactiva. Esta contribución fue publicada en el artículo *"A FACTS devices allocation procedure attending to load share"*, en la revista Energies, en 2020 [165].

- En el capítulo 5 se propone una metodología para el análisis del impacto de los dispositivos FACTS en sistemas eléctricos teniendo en cuenta las variaciones en la demanda. Esta metodología se basa en la *Mejora Relativa Media* de una serie de índices para evaluar las soluciones y en la optimalidad de Pareto para la toma de decisiones. Además, esta metodología incluye un método para la selección de índices basado en la Información Mutua. Tanto el desarrollo de esta metodología como los resultados obtenidos están incluidos en un artículo científico que será enviado para su publicación en breve.

- En el capítulo 6 se ha probado que la metodología propuesta permite considerar las variaciones de la demanda tanto para la ubicación de dispositivos FACTS como para la selección de su referencia de control de tensión. Se ha demostrado la influencia de las variaciones de la potencia total de los escenarios demanda y su distribución en la ubicación y configuración de los dispositivos FACTS. Por otra parte, se han encontrado discrepancias importantes entre la solución propuesta y el enfoque basado en el escenario punta. Se ha demostrado que, cuando se usan escenarios de demanda con distribución variable, el escenario "punta" puede no ser el caso más desfavorable. Es importante resaltar que este enfoque puede generalizarse para analizar otros problemas de planificación de la expansión de sistemas eléctricos, como la ubicación de generadores renovables, puesto que no se han hecho consideraciones particulares para el problema estudiado. Está previsto incluir los resultados de la utilización de esta metodología para la ubicación de generadores renovables en un artículo científico para su publicación en breve.

- En el capítulo 6 se ha validado el método propuesto para la selección de índices. Este método se basa en la Información Mutua y ha proporcionado resultados que son coherentes con las preferencias de los investigadores para este tipo de estudios, de acuerdo con la revisión bibliográfica. Es importante también mencionar que este método puede ser utilizado para la selección de índices en distintos ámbitos, pues se basa en la información que comparten desde un punto de vista estadístico. Está previsto incluir los resultados de la utilización de esta metodología para la ubicación de generadores renovables en un artículo científico para su publicación en breve.

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