**UNIVERSITY OF SÃO PAULO
SÃO CARLOS SCHOOL OF ENGINEERING**

Tiago Soares Vitor

**Efficient Evolutionary Algorithms for Robust Volt/VAr
Control in Modern Power Distribution Systems**

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Tiago Soares Vitor

**Efficient Evolutionary Algorithms for Robust Volt/VAr
Control in Modern Power Distribution Systems**

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Concentration Area: Electrical Power Systems

Advisor: Prof. Dr. José Carlos de Melo Vieira Júnior

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This work is dedicated to

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for their lifelong teachings, which inspire me to give my best
for what is noble and honorable.*

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*“Make things happen. Do not be afraid to make a mistake.
But if you make a mistake, repent yourself of that, set things right, and move forward.”*
Dong Yu Lan

ABSTRACT

VITOR, T. S. **Efficient Evolutionary Algorithms for Robust Volt/VAr Control in Modern Power Distribution Systems**. 2021. 198p. Thesis (Ph.D.) - São Carlos School of Engineering, University of São Paulo, São Carlos, 2021.

Modern power distribution systems have posed new challenges to Volt/VAr control strategies due to the increasing penetration of distributed generation (DG) units. But, with the advent of smart grid technologies, these systems have also provided remarkable opportunities for the development of new optimization and energy saving techniques. In this context, this thesis presents a new specialized evolutionary system for Volt/VAr optimization (SES-VVO) to efficiently solve the multi-objective optimization problem (MOP) when the number of tap-changing operations of voltage regulating devices is considered together with the conservation voltage reduction (CVR) goals. This problem is a challenging task for evolutionary algorithms (EAs) in terms of meeting voltage limits constraints and reaching near optimal solutions. Specialized search mechanisms were developed to improve the overall performance of the day-ahead operation planning and the hourly decision-making approaches, giving more realistic and cost saving solutions for distribution systems' operators. The SES-VVO also corroborated with the development of an advanced strategy that has potential for real-time operation considering the stochastic behavior of load/DG variables. Further results demonstrated that the tap change costs have a decisive impact on the economics of VVO-based CVR. Additionally, this thesis investigates and proposes a novel robust framework — constituted by parameters and metrics — to quantitatively estimate how robust is a VVO solution when facing the stochastic nature of load/DG uncertainties. The analysis demonstrated that the VVO solutions designed to specifically search for CVR goals, both in energy and cost savings, are sensitive to these uncertainties, leading to violation of voltage standards. So, as the integration of DG is evermore increasing in distribution systems, uncertainty realizations can lead to poor voltage quality in non-robust VVO designs. To tackle this problem, the proposed parameters/metrics were incorporated into the VVO-based CVR via MOP. Thus, a balance between performance and robustness could be achieved through trade-off solutions, followed by a decision-making based on the used-preferred level of robustness. The results showed that at the expense of a small amount of energy and operating cost, greater robustness can be obtained to face the uncertainties. In summary, the proposed methods in this thesis are promising for smart grid applications, being capable of finding robust and cost-effective CVR solutions on a real-time scale.

Keywords: Conservation voltage reduction. Distributed generation. Distribution systems. Evolutionary multi-objective optimization. Robust design. Volt/VAr control.

RESUMO

VITOR, T. S. **Algoritmos Evolutivos Eficientes para o Controle Volt/VAr Robusto em Sistemas Modernos de Distribuição de Energia Elétrica.** 2021. 198p. Tese (Doutorado) - Escola de Engenharia de São Carlos, Universidade de São Paulo, São Carlos, 2021.

Os modernos sistemas de distribuição de energia elétrica têm imposto novos desafios às estratégias de controle Volt/VAr devido à crescente penetração de unidades de geração distribuída (DG). Com o advento das tecnologias de rede inteligentes, esses sistemas também têm proporcionado oportunidades notáveis para o desenvolvimento de novas técnicas de otimização e economia de energia. Neste contexto, esta tese apresenta um novo sistema evolutivo especializado em otimização Volt/VAr (SES-VVO) para resolver eficientemente o problema de otimização multiobjetivo (MOP) quando o número de operações de comutação dos dispositivos reguladores de tensão é considerado em conjunto com os objetivos da redução da tensão de conservação (CVR). Este problema é uma tarefa desafiadora para os algoritmos evolutivos (EAs) em termos de atendimento às restrições de limites de tensão e obtenção de soluções quase ótimas. Mecanismos de busca especializados foram desenvolvidos para melhorar o desempenho geral do planejamento da operação do dia seguinte e das abordagens de tomada de decisão a cada hora, fornecendo soluções mais realistas e econômicas para os operadores dos sistemas de distribuição. O SES-VVO também corroborou com o desenvolvimento de uma estratégia avançada que tem potencial para operação em tempo real considerando o comportamento estocástico das variáveis de carga e DG. Resultados adicionais também demonstraram que os custos de comutação têm um impacto decisivo na parte econômica do CVR baseado em otimização Volt/VAr. Além disso, esta tese propõe um novo arcabouço conceitual de robustez — constituído por parâmetros e métricas — para estimar quantitativamente o quão robusta é uma solução VVO quando enfrenta a natureza estocástica das incertezas de carga e DG. A análise demonstrou que as soluções VVO projetadas para buscar especificamente os objetivos do CVR, tanto em termos de economia de energia quanto de custos, são sensíveis a essas incertezas, levando à violação das restrições de tensão. Portanto, como a integração de DG está aumentando cada vez mais nos sistemas de distribuição, as incertezas podem levar à baixa qualidade da tensão em projetos não robustos de VVO. Para resolver este problema, os parâmetros e métricas de robustez foram incorporados à estratégia de CVR, e modelados como um problema de otimização multiobjetivo. Assim, um equilíbrio entre desempenho e robustez pôde ser alcançado por meio de soluções de compromisso (*trade-off*), seguido por uma tomada de decisão com base no nível de robustez especificado. Os resultados demonstraram que às custas de uma pequena quantidade de energia e custo operacional, pode-se obter maior robustez para enfrentar as incertezas. Em resumo, os

métodos propostos nesta tese são promissores para aplicações em redes inteligentes, sendo capazes de encontrar soluções CVR robustas e econômicas em escala de tempo real.

Palavras-chave: Redução de tensão conservativa. Geração distribuída. Sistemas de distribuição. Otimização evolutiva multiobjetivo. Projeto robusto. Controle Volt/VAr.

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LIST OF ABBREVIATIONS AND ACRONYMS

AMI	Advanced Metering Infrastructure
ANEEL	Brazilian Electricity Regulatory Agency
AVR	Automatic Voltage Regulator
C-MOPSO	Complete (Horizon) Multi-Objective Particle Swarm Optimization
CB	Capacitor bank
COM	Component Object Model
Conv-VR	Conventional Voltage Regulation
CVR	Conservation Voltage Reduction
DER	Distributed Energy Resource
DG	Distributed Generation
DM	Decision Making
DM-SES-VVO	Decision Making based on the SES-VVO
DMS	Distribution Management System
EA	Evolutionary Algorithm
EMO	Evolutionary Multi-Objective Optimization
ESD	Energy Storage Device
ESS	Energy Storage System
EV	Electric Vehicle
GA	Genetic Algorithm
GIS	Geographic Information System
HTP	Holding Tap Position
IED	Intelligent Electronic Device
IVVC	Integrated Volt/VAr Control
LDC	Line Drop Compensator

MDMS	Meter Data Management System
MOEA	Multi-Objective Evolutionary Algorithm
MOGA	Multi-Objective Genetic Algorithm
MOP	Multi-Objective Optimization Problem
MOPSO	Multi-Objective Particle Swarm Optimization
NSGA-II	Nondominated Sorting Genetic Algorithm II
OC	Operating costs
OLPF	On-line Power Flow
OLTC	On-Load Tap Changer
OP	Operation Planning
OpenDSS	Open-source Distribution System Simulator
OP-SES-VVO	Operation Planning based on the SES-VVO
PV	Photovoltaic
RES	Renewable Energy Sources
RTU	Remote Terminal Unit
R-MOPSO	Rolling (Horizon) Multi-Objective Particle Swarm Optimization
SA	Scenario Aggregation Method
SC	Switched Shunt Capacitor
SCADA	Supervisory Control and Data Acquisition
SES-VVO	Specialized Evolutionary System for VVO
SOP	Single-Objective Optimization Problem
SOP-SES-VVO	Single-Objective Optimization Problem based on the SES-VVO
SVR	Step Voltage Regulator
TAI	Temporary Artificial Individual
VVC	Volt/VAr Control
VVMO	Volt/VAr Multi-Objective Optimization
VVO	Volt/VAr Optimization

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1 INTRODUCTION

Volt/VAr control (VVC) is a crucial business for distribution management systems. According to [Tahir et al. \(2016\)](#), a proper selection and coordination of equipment for controlling voltage and reactive power are among the major challenges of power system engineering. The main role of Volt/VAr control is no doubt to keep the steady state voltage in all nodes of the system within acceptable limits all the time. But this concept has evolved. Besides high-quality power supply, enhanced goals have been added in order to improve the overall system efficiency. As a result, many researchers have concentrated efforts to develop new intelligent and advanced schemes, giving a modern interest to this topic ([ULUSKI, 2010b](#); [VITOR](#); [ASADA](#); [VIEIRA, 2020](#)). Indeed, this renewing focus opens a wide range of possibilities for applications.

To illustrate, although Volt/VAr control has been widely studied and experienced for decades, new paradigms have demanded updated Volt/VAr control strategies to face the new operating scenario challenges, which include power electronic devices and distributed energy resources (DERs) ([MELLO](#); [PFITSCHER](#); [BERNARDON, 2017](#); [PAMSHETTI](#); [SINGH, 2019](#)), and to make use of the technological advances in infrastructure, like advanced metering infrastructure (AMI) and distribution management system (DMS) ([MANBACHI et al., 2016a](#)). Therefore, new opportunities and challenges are still opened to be studied ([MARKUSHEVICH, 2011](#)).

Volt/VAr control is a complex process that involves multiple voltage regulating devices working collaboratively to achieve certain objectives ([RANAMUKA](#); [AGAL-GAONKAR](#); [MUTTAQI, 2014](#)). The conventional devices employed in this technique are: on-load tap changer (OLTC), step voltage regulators (SVRs) and switchable shunt capacitors (SCs). Essentially, the success of the Volt/VAr control depends on the proper coordination among them.

An important way to pursue optimal results is by formulating the Volt/VAr control as an optimization problem. That is why many times this scheme is known as Volt/VAr optimization (VVO) ([BORGHETTI](#); [NAPOLITANO](#); [NUCCI, 2015](#)). In general, the VVO is defined as the optimal control of the system's equipment (e.g., OLTC, SVRs, and SCs) so that certain objectives can be achieved, such as: loss minimization, voltage profile improvement, and conservation voltage reduction ([AHMADI](#); [MARTI](#); [DOMMEL, 2015](#); [SENJYU et al., 2008](#); [PADILHA-FELTRIN](#); [RODEZNO](#); [MANTOVANI, 2015](#)). In fact, Volt/VAr control fits very well in optimization problems. The complete design comprises not only the distribution system operator goals, which are modeled by the objective functions, but also several restrictions related to economic, security, and operational subjects that can be handled by the constraints.

Several problems have been treated as Volt/VAr optimization. An early work recommended a centralized Volt/VAr control algorithm for optimizing the distribution system management (ROYTELMAN; WEE; LUGTU, 1995). Since then, many methods for VVO have been proposed following this principle. But recently, huge advances were incorporated into the centralized optimization structure enhancing its features and the capability of dealing with Volt/VAr control problems.

In this context, much importance has been given to the distributed generation (DG) units based on renewable energy sources (RES) (NIKNAM; ZARE; AGHAEI, 2012). Initially, former researches focused only in designing the control coordination in the presence of DG (SENJYU et al., 2008), aiming to reduce DG impacts and further maximize the DG capacity that can be supported by the existing network assets (OCHOA; DENT; HARRISON, 2010). But with the deployment of the smart grid technologies, elaborated controls have been considering the DG actively participating in the coordinated voltage control (KIM et al., 2013; KULMALA; REPO; JARVENTAUSTA, 2014), driving the evolution of power distribution systems from passive to active distribution networks (PILO et al., 2014). For this purpose, real and reactive powers of DGs are considered as control variables together with the conventional ones of OLTC, SVRs and SCs. Additionally, modern devices and special loads have been engaged in a more comprehensive design framework. For instance, energy storage device (ESD) and electric vehicle (EV) are considered in the innovative solutions of VVO (SABILLON-ANTUNEZ et al., 2017; MANBACHI et al., 2016a). In all these cases, Volt/VAr control has proved efficient to deal with the new challenges which emerge in the modern distribution systems. Indeed, the trend is beyond accommodating these components to minimize impacts, but further to benefit from them.

Equally important, DMS and AMI have been developed to make distribution networks more reliable and more efficient (MANBACHI et al., 2014). They provide essential features that VVO requires, such as, communication infrastructure and optimized decision-making system. Based on these technologies, the most advanced Volt/VAr control framework can be implemented, namely, the integrated Volt/VAr control (IVVC), also known as DMS-based Volt/VAr control (RAHIMI; MARINELLI; SILVESTRO, 2012). The IVVC is a topology that offers a complete framework for VVO implementation. It can upgrade conventional VVO systems by using new smart grid features — such as ESD, EV and other DERs — into advanced VVO solutions (MANBACHI et al., 2017). Thus, intelligent systems can be built on this advanced centralized framework, providing the computational efficient optimization engine for VVO applications.

Moreover, Volt/VAr control can be designed for either real-time or planning operations of power distribution systems (EVANGELOPOULOS; GEORGILAKIS; HATZIARGYRIOU, 2016). In the real-time operation, actions and commands occur in short time

periods based on communication signals, state-estimation algorithms and decision support systems. Whereas, the scheduled (or planning) operation programs the day-ahead schedule of the coordinated control based on the forecasting curves of load demand and renewable power generation processed by robust algorithms. Both operations are supported by the IVVC framework. But, due to the modernization of distribution systems, there is a demand for real-time optimization solutions (ZAFAR et al., 2020).

Notably, the VVO is a challenging optimization problem due to inherent characteristics of the operation, such as: integer decision variables, multiple and nonlinear objectives, non-convex objectives and solution set, high-dimensional search space and nonlinear constraints, large number of variables, coordination of various control devices with different time frames, multi-period constraints, and uncertainties of renewable-based DGs and load forecasts (FENG; PETERSON, 2010; ZHOU et al., 2017; VASCONCELOS, 2017). Formulating real-world problems as reliable as possible means to consider multi-objectives, which are usually in conflict with each other, and to design robust solutions capable to face uncertainties of load/DG variables. So, selecting an adequate and non-computationally expensive solution for VVO problems is the core attribute of the integrated Volt/VAr control optimization (RAHIMI; MARINELLI; SILVESTRO, 2012; GENC; BAGGU, 2014). That is why many researchers have focused on making the algorithms and implementation techniques more efficient (MANBACHI et al., 2016a) and robust against the uncertainties (ZHANG et al., 2019).

Research gaps have been identified in the literature review undertaken throughout this thesis. In the examined works, the integration of conservation voltage reduction (CVR) goals and efficient tap change operations has not been designed as multi-objective optimization problems (MOPs) to be solved by evolutionary multi-objective optimization (EMO) algorithms. Moreover, the following research gaps and opportunities on the multi-objective VVO designs could be highlighted:

- a) specialized mechanisms of search to improve the overall efficiency of EAs;
- b) reference metric to access the quality of the solutions;
- c) intelligent strategies that do not only depend on fast-acting devices (e.g., smart inverters) to face the load/DG uncertainties;
- d) studies about the tap-changing operations costs impacts considering the CVR strategy;
- e) comprehensive model to design the day-ahead operation planning (OP) and the hourly decision-making (DM) approaches;
- f) robust metrics to model load/DG uncertainties supported by the VVO design;
- g) methods for designing robust VVO solutions that do not rely on stochastic programming or robust optimization approaches;

- h) techniques for estimating the costs associated with improving the robustness of VVO designs.

In summary, due to the smart grid context, tackling the new paradigms on the planning and operation procedures of power distribution systems depends upon updated Volt/VAr control strategies to face the new operating scenarios challenges and to make use of the technological advances in infrastructure. This is the background and context for the thesis research, which pursues to fill the above-mentioned research gaps by the following objectives and contributions.

1.1 Research objectives and hypothesis questions

Designing Volt/VAr control strategy as a multi-objective optimization problem is an important way to achieve high quality power supply and, at the same time, meet desired performance goals on distribution systems. Moreover, to operate under real-world conditions, the Volt/VAr control design must be capable of facing uncertainties related to the variation of load demand and the intermittence of DG generation. Therefore, this thesis addresses the following general and specific objectives:

General objective:

The aim of this thesis is to propose Volt/VAr control methods based on evolutionary optimization algorithms to deal in a robust and efficient way with the uncertainties of renewable sources and loads, when the energy efficiency is the major concern, and that such methods are suitable for real time applications.

Specific objectives:

1. Model the Volt/VAr control as multi-objective optimization problems (MOPs), named Volt/VAr multi-objective optimization (VVMO), and, based on evolutionary algorithms (EAs), propose computationally efficient methods to solve these problems.
2. Design Volt/VAr control solutions that are robust against uncertainties and, at the same time, economic to operate the system.

Some *hypothesis questions* that arise, but are not limited to, from the **research objectives** are as follows:

1. How efficient the standard EAs are in solving the VVMO problem?
2. Is it possible to create new search engines that improve the performance of the EAs when solving the VVMO?
3. How important it is to model the number of tap-changing operations of voltage regulating devices into the objective functions?

4. How robust is a Volt/VAR control solution against uncertainties?
5. How to measure the robustness of a solution?
6. Is a robust solution economically viable?

In general, the proposals must attain to smart grid expectations, that is, the solutions must face the new operating scenario challenges (e.g., the deployment of DERs) and make use of the technological advances in infrastructure (e.g., AMI and DMS) in view of real-time applications.

1.2 Main contributions

This research models the Conservation Voltage Reduction (CVR) based on VVMO problems. To solve them, it is proposed a specialized evolutionary system for VVO (SES-VVO) in [Chapter 4](#). Moreover, once established the SES-VVO method, this research goes on to propose a novel robustness framework in [Chapter 5](#) and to study the costs associated with robustness in [Chapter 6](#). In summary, this thesis provides the following main contributions:

- a mathematical formulation that allows the development of advanced search mechanisms to meet voltage limit constraints and reach near optimal solutions. These search mechanisms are proposed especially to: 1) restrict search space, 2) effectively satisfy voltage constraints, 3) efficiently minimize the tap-changing operations, 4) efficiently minimize the active power intake on the system, and 5) better cover the Pareto front promoting solution diversity;
- an advanced strategy for decision-making that can speed up the search for higher efficient solutions and that presents robustness to face load/DG forecast deviation;
- the demonstration that the tap-changing costs have a decisive impact on the economics when the CVR goals are pursued by the VVO proposed approach.
- a robustness framework, constituted by parameters and metrics, to quantitatively estimate how robust is a VVO solution when facing the stochastic nature of load/DG, permitting the development of multi-objective approaches to robustness optimization;
- the demonstration that the VVO-based CVR solutions are sensitive to load/DG uncertainties, but at the expense of a small amount of energy and operating cost, greater robustness can be obtained to face these uncertainties;
- a way to estimate the costs associated with improving the robustness of VVO designs so that cost-effective robust CVR solutions may be designed.

1.3 Thesis outline

This thesis is organized in seven chapters and appendix, of which:

- **Chapter 1** is an introduction to the thesis research;
- **Chapter 2** presents the definition of Volt/VAr control, from basic concepts to advanced topics. First, three well-established objectives are discussed. Then, the main approaches of Volt/VAr control are detailed in order to lay the foundation for the centralized control framework in which the proposed methods will rely on. And finally, this chapter identifies the open issues on the optimal Volt/VAr control;
- **Chapter 3** gives an overview of the multi-objective optimization theory in the form of definitions. First, the MOPs are defined using formal formulations. Basic terminology, concepts, set of symbols, and formal relationships are explained. Then, the general characteristics of the class of multi-objective evolutionary algorithms (MOEAs) are presented. Moreover, reasons for "Why evolutionary?" are discussed;
- **Chapter 4** presents the new optimization algorithm (SES-VVO) to efficiently solve the MOP when the number of tap-changing operations of voltage regulating devices is considered together with the CVR goals. Simulations are carried out on the IEEE 34-bus system in the presence of photovoltaic (PV) generation to validate the proposal, including studies of feasibility, performance, Pareto front approximation, costs, and uncertainties. Also, comparisons with other methods are conducted to clarify the effectiveness of the proposed method. In addition, the potential for real-time applications is investigated;
- **Chapter 5** investigates and proposes a novel robustness framework — constituted by parameters and metrics — to quantitatively estimate how robust is a VVO solution when facing the stochastic nature of load/DG uncertainties. Initially, this chapter focuses on showing how sensitive the operation of the system is in the face of uncertainties when CVR goals are strictly pursued. Then, a robust VVO-based CVR is proposed by incorporating the parameters/metrics into the optimization. Simulations are carried out on the IEEE 123-bus system in the presence of PV generation to validate the proposals. Additional studies are included in this chapter to check the CVR effectiveness, energy savings, and the robustness for scenario realizations of the uncertainties;
- **Chapter 6** conducts a case study to investigate the costs associated with improving the robustness of the VVO-based CVR. For this, a way of estimating robustness costs is proposed. Then, four methods are considered for comparison purposes, including a benchmark robust method from literature and a proposed method based on the

robustness framework. Simulations are carried out on the IEEE 123-bus system in the presence of PV generation to perform the case study under heavy demand. Besides the costs analyses, additional studies are included in this chapter to check the CVR effectiveness, energy savings, the robustness for scenario realizations of the uncertainties, and computational efforts. This chapter fulfills the ultimate goal of this thesis by providing a promising method for smart grid applications capable of finding robust and cost-effective CVR solutions on a real-time scale;

- **Chapter 7** presents the general conclusions and suggestions for future works;
- **Appendix A**, **Appendix B**, and **Appendix C** present test feeders, input data for the Volt/VAr control simulations, parameters for conventional voltage regulation, and daily tap solutions.

As an **important note**, it is worth mentioning that the literature review is not gathered in just one chapter, but distributed throughout the thesis.

1.4 Publications

The extended review of Volt/VAr control in modern distributions systems (**Chapter 2**) and applications with EAs (**Chapter 3**) were published by the following book chapter Vitor, Asada and Vieira (2020):

- VITOR, T. S.; ASADA, E. N.; VIEIRA, J. C. de M. Optimal Volt/Var control applied to modern distribution systems. In: RESENER, M. et al (Ed.). **Handbook of Optimization in Electric Power Distribution Systems**: Springer, Cham, Feb 2020, (Energy Systems). p. 1–56. ISBN 978-3-030-36115-0. Available at: https://doi.org/10.1007/978-3-030-36115-0_1.

The proposed specialized evolutionary system for Volt/VAr optimization (SES-VVO) and other results of **Chapter 4** were published in an international journal by the following research paper Vitor and Vieira (2021b):

- VITOR, T. S.; VIEIRA, J. C. M. Operation planning and decision-making approaches for Volt/Var multi-objective optimization in power distribution systems. **Electric Power Systems Research**, v. 191, p. 106874, Feb 2021. ISSN 0378-7796. Available at: <http://www.sciencedirect.com/science/article/pii/S0378779620306726>.

Partial results of the proposed robustness metric (**Chapter 5**) were published in the following conference proceedings Vitor and Vieira (2018):

- VITOR, T. S.; VIEIRA, J. C. M. A robust Volt/Var control via multi-objective optimization. In: **2018 13th IEEE International Conference on Industry Applications (INDUSCON)**. São Paulo, Brazil: IEEE, 2018. p. 672–678. Available at: <https://doi.org/10.1109/INDUSCON.2018.8627297>.

Partial results of the proposed robustness cost ([Chapter 6](#)) were accepted for the following conference proceedings [Vitor and Vieira \(2021a\)](#):

- VITOR, T. S.; VIEIRA, J. C. M. Cost Analysis of Robust Volt-Var Control Designs. In: **2021 IEEE Power and Energy Society General Meeting**. Washington, DC, USA: IEEE, 2021. In press.

During the development of this thesis work, other results were published in the following conference proceedings [Vitor and Vieira \(2016a\)](#), [Vitor and Vieira \(2016b\)](#):

- VITOR, T. S.; VIEIRA, J. C. M. Optimal voltage regulation in distribution systems with unbalanced loads and distributed generation. In: **2016 IEEE Innovative Smart Grid Technologies - Asia (ISGT-Asia)**. Melbourne, VIC, Australia: IEEE, 2016. p. 942–947. Available at: <https://doi.org/10.1109/ISGT-Asia.2016.7796512>;
- VITOR, T. S.; VIEIRA, J. C. M. Regulação ótima de tensão para sistemas de distribuição com desbalanceamento de cargas na presença de geração distribuída. In: **XXI Congresso Brasileiro de Automática - CBA2016**. Vitória, ES: SBA, 2016. p. 1602–1607. Available at: <https://plataforma.swge.com.br/PROCEEDINGS/PDF/CBA2016-0470.pdf>.

2 VOLT/VAR CONTROL

Volt/VAr control is one of the most important schemes in the management and operation of distribution systems. It refers to techniques of using voltage regulating devices and reactive power controls, existing in the substations and feeders, to keep consumer's voltage levels within the acceptable ranges for various loading conditions and under the increasing penetration of renewable energy sources (RES). This key operating task is responsibility of the distribution utilities, which have the goal of providing reliable high-quality power supply in an efficient manner.

Although the basic definition of Volt/VAr control is related to voltage regulation, more elaborated goals can be explored to improve the overall system efficiency. This is mainly accomplished by formulating the Volt/VAr control as an optimization problem. Thus, besides the voltage regulation issues, additional objectives — such as minimal electrical losses, reduced energy consumption, and minimal voltage deviations (ULUSKI, 2010b; PADILHA-FELTRIN; RODEZNO; MANTOVANI, 2015) — can be included into the optimization problem formulation. This enhanced function, well-known as Volt/VAr optimization (VVO), opens a wide range of opportunities for the Volt/VAr control. Furthermore, due to the expansion of smart grid applications, the Volt/VAr control has received increasing attention from researchers looking for advanced solutions to face the new operating scenarios challenges and to make use of the smart grid technologies.

In this context, the aim of this chapter is to present the Volt/VAr control, from basic concepts to advanced topics, in which the proposed methods of this thesis rely on.

2.1 Volt/VAr control objectives

Volt/VAr control has the complex task of coordinating a series of devices to work collaboratively in order to achieve some operating objectives. In this section, the following well-established objectives, which are related to service quality and power supply efficiency, are introduced: voltage profile improvement, loss reduction, and conservation voltage reduction.

2.1.1 Improvement of voltage profile

Voltage is a fundamental electrical parameter to evaluate the quality of power distribution supply. If voltage levels are out of the permitted operating ranges defined by standards, the following issues can occur (SYED; SYED, 2016; DAS, 2016): a) poor operation of the power system; b) reduced performance of the equipment; c) damage to utility equipment and customer loads; d) safety hazard; and e) trigger protection equipment.

In general, the voltage must be controlled within the desired range, flattening the voltage profile of feeders (LI et al., 2017).

The improvement of the overall voltage profile of the distribution system is accomplished by means of voltage regulating devices and capacitors at the substation and along the feeders (GERS, 2013). The ratio of the tap-changing transformers can be changed to improve the voltage profile of the feeder, meanwhile shunt capacitors can be switched to compensate the reactive power demand and thereby reduce the voltage drops. Because of this integration between voltage and reactive power controls, this method is well-known as Volt/VAr control. It is important to point out that the effect of varying loads and RES impacts on voltage drop and voltage variation (VIAWAN, 2008), challenging the Volt/VAr control scheme.

2.1.2 Loss reduction

In the process of delivering energy to final customers, electrical losses occur naturally in the components of the system (lines, transformers, capacitors, etc.). These losses, which are mainly represented by power dissipation, are known as technical losses and they are the emphasis of the Volt/VAr control. So, the technical losses P_{Loss} in the distribution network can be given by:

$$P_{Loss} = \sum_{T \in \Omega_T} P_{Loss,T} + \sum_{R \in \Omega_R} P_{Loss,R} + \sum_{j \in \Omega_B} R_j I_j^2 \quad (2.1)$$

where Ω_T and Ω_R are the sets of step-down transformers and voltage regulators, Ω_B is the set of branches, and R_j and I_j are the resistance and current of the j th branch.

Based on equation (2.1), there are two straight ways to reduce losses: by reducing resistance of lines and/or reducing currents in lines. Here, the focus is to bring down technical losses by decreasing the reactive component of the line current (AGUERO, 2012). This is accomplished conventionally by switched capacitors that fulfill the Var control portion of Volt/VAr control (ROYTELMAN; GANESAN, 2000; HU et al., 2003).

While the power losses at the peak time may restrict further attendance of loads and increase the requirement of generating capacity, the energy losses require additional energy over the demand of loads. The reduction of losses brings benefits to both utility and customers, due to cost savings, and can lead to better service quality by improving the voltage profile.

2.1.3 Conservation voltage reduction

Conservation voltage reduction (CVR) refers to the method of lowering the voltage magnitudes in the distribution system to reduce peak demand, losses, and energy consumption in a way that meets power quality standards. This technique permits to

promote energy savings without expecting changes in customer's consumption behavior (MANBACHI et al., 2016b). Because CVR goals perfectly match the Volt/VAr control objectives, new solutions have considered CVR as part of the Volt/VAr control through a comprehensive objective (MANBACHI et al., 2016a). Thus, energy efficiency can be consistently improved by maintaining voltage levels on the lower limits of standard range. Successful real world studies have reported a demand reduction ranging from 1% to 6% in the total demand due to CVR implementation (AHMADI; MARTI; DOMMEL, 2015). In fact, CVR is one of the most cost-effective ways to save energy in distribution systems (WANG; WANG, 2014a).

One way of estimating the CVR effects is by computing the CVR factor (CVR_f), which is defined as the percentage reduction of energy consumption caused by 1% reduction of voltage (SEN; LEE, 2016):

$$CVR_f = \frac{\Delta \text{kWh}[\%]}{\Delta V[\%]} \quad (2.2)$$

This shows that the voltage dependency of loads is the key aspect for CVR effectiveness. Nonetheless, in distributions systems, loads are normally modeled as voltage dependent, like constant impedance or constant current models, to provide a suitable representation of the network operation (SABILLON-ANTUNEZ et al., 2017).

Indeed, the assessment of CVR effects is crucial for cost-benefit analysis. Other issues raised by Wang and Wang (2014a) are related to the need for optimal coordination among the Volt/VAr devices to reduce voltage in a reliable way, while dealing with DG penetration, and employing the capabilities provided by smart grid technologies.

2.1.3.1 CVR benefits

In general, utilities are constantly challenged by the ever-increasing energy demand. To deal with this issue, two approaches can be implemented (HAFEEZ et al., 2020): generation side management (GSM) or demand side management (DSM). GSM is related to increasing the power generation. However, there is an increased pressure to reduce fossil fuel-based energy generation, which further leads to CO₂ emission. On the other hand, DSM methods involve management of users' energy consumption, like: demand response (DR) programs, load management, and, more recently, the use of DERs (NAZEMI et al., 2020). Moreover, energy efficiency techniques, like CVR, may be utilized to defer distribution capacity expansion (HOSSAN; CHOWDHURY, 2019). In other words, CVR may delay the building of new power-plants and/or system reinforcements by offsetting the increased demand (DIAZ-AGUILÓ et al., 2013).

Since the 70's in different countries, several utilities have demonstrated the effectiveness of CVR deployment (WANG; WANG, 2014a; WANG; WANG, 2014b). It is straightfor-

ward that CVR directly benefits customers by reducing energy bills ([GUTIERREZ-LAGOS; OCHOA, 2019](#)). But, from the point of view of practitioners, skepticism may be raised, since the revenues of utilities are determined by the income selling energy. However, when considering the ongoing efforts in grid modernization, utilities may experience several benefits, summarized as ([WANG; WANG, 2014a](#)):

- peak loading relief of distribution network;
- net loss reduction (considering both the transformers and distribution lines);
- potential incentives and requirements from regulatory bodies;
- increasing social welfare such as fuel consumption and emission reduction; and
- CVR can be combined with the optimal Volt/VAr control.

2.1.3.2 Voltage dependency of loads

Traditionally, loads in distribution systems are represented as one of the following three types: constant impedance (Z), constant current (I) or constant power (P). Details of these models can be found in [Satsangi and Kumbhar \(2016\)](#). The mathematical values of their corresponding CVR factors ([Equation 2.2](#)) are equal to 2.0, 1.0, and 0.0, respectively, where the active load power is proportional to voltage, like ([SEN; LEE, 2016](#)):

$$P \propto V^{CVR_f} \quad (2.3)$$

So, there is a direct relation between voltage and demand in models Z and I (quadratically and linearly, respectively), resulting in CVR benefits when voltage is reduced. In contrast, although the demand of model P does not change, lower voltage increases current, which means higher losses across the feeder. Nonetheless, laboratory experiments have demonstrated that, in reality, each appliance (or piece of equipment) in the system has its own P - V characteristics, being a composition of these three types of constant loads ([DIAZ-AGUILÓ et al., 2013](#)). Thus, for real-world applications, the CVR factor will be in the range from 0.0 to 2.0.

Therefore, the CVR benefits depend on the voltage sensitivity of the electrical loads, which can also be represented using two voltage dependent load models: exponential and polynomial (or ZIP) models. They are respectively expressed as ([HOSSAN; MARUF; CHOWDHURY, 2017](#)):

$$P_i = P_{n,i} \left(\frac{V_i}{V_n} \right)^{n_i^P} \quad (2.4)$$

$$P_i = P_{n,i} \left[Z_i^P \left(\frac{V_i}{V_n} \right)^2 + I_i^P \left(\frac{V_i}{V_n} \right) + P_i^P \right] \quad (2.5)$$

where, for each bus i , P_i is the active load power at operating voltage V_i and $P_{n,i}$ is the active load power at nominal voltage V_n ; while the load-to-voltage sensitivity in the exponential model (Equation 2.4) depends on the exponential factor n_i^P , this sensitivity in the ZIP model (Equation 2.5) depends on the combination of constant impedance Z_i^P , constant current I_i^P and constant power P_i^P characteristics of the load, where $Z_i^P + I_i^P + P_i^P = 1$.

As the relationship between bus voltage and load power of these models is expressed at a given instant of time, the exponential and ZIP models are addressed as static models. Many studies have been conducted to characterize the parameters of Equation 2.4 and Equation 2.5 and, thus, describe the voltage-dependent behavior of different types of loads (SEN; LEE, 2016; BOKHARI et al., 2014). Although both models have been widely adopted in the literature, the exponential model is more likely to be used when detailed load information is not available (SINGH; PAMSHETTI; SINGH, 2019), whereas the ZIP model, when more accuracy is required to quantify the CVR effects (HOSSAN; MARUF; CHOWDHURY, 2017). Anyway, as most of the loads in distribution network are predominantly voltage dependent (GUTIERREZ-LAGOS; OCHOA, 2019), the CVR deployment may provide consistent benefits for both utilities and costumers.

2.2 Volt/VAr control approaches

According to monitoring and control capabilities deployed in the distribution system, the Volt/VAr control can be classified into the three approaches (ULUSKI, 2010b): Traditional Volt/VAr control, SCADA-based Volt/VAr control, and Integrated Volt/VAr control.

2.2.1 Traditional Volt/VAr control

Traditional Volt/VAr control uses local measurements of voltage and current to control electromechanical devices (OLTC, SVRs and SCs) based on independent stand-alone controllers (ULUSKI, 2010b; GONEN, 2014). The aim is to accomplish basic objectives, like meeting voltage standards and improving power factor, in radial distribution networks.

Strengths of traditional Volt/VAr control approaches include (LI et al., 2019; ULUSKI, 2011): low-cost implementation, minimal learning curve required, scalability, and not relying on field communications. Weaknesses of such approaches include (LI et al., 2019; ULUSKI, 2011; ULUSKI, 2010b): no self-monitoring features, non-optimal system operation, lack of “visibility” of remote conditions at the grid edge, inflexible to respond

to changing conditions on the distribution feeders, inability to override control actions during power system emergencies, and ineffective to deal with DG penetration.

2.2.1.1 On-load tap changer transformer

The on-load tap changer permits to change the transformer ratio of the substation transformer without interrupting the service (VIWAN, 2008; DAS, 2016). When the automatic voltage regulator (AVR) senses that the secondary voltage is no longer within the permitted margin, tap position is changed to restore the required voltage (SMITH; REDFERN; POTTS, 2003). A time delay aids to avoid unnecessary tap position changes due to transient voltage variations (SON et al., 2000). Moreover, the line drop compensator (LDC) can be applied to ensure the correct voltage at a distant load by simulating the voltage drop across the feeder.

2.2.1.2 Step voltage regulator

The step voltage regulator, which is an auto-transformer for voltage control purposes, has provision for correcting voltage at the load center (or regulator bus) by automatically changing the taps of its series winding when voltage exceeds the $\pm$ one-half of the bandwidth (KUNDUR, 1994; GONEN, 2014). Besides the desired voltage and bandwidth, other settings are related to the time delay for preventing unnecessary tap changes and the internal model of the LDC (R and X) for compensating the voltage drop between the regulator and the load center (KERSTING, 2001a). Usually, 32 steps permit a voltage regulation range of $\pm 10\%$ (SHORT, 2004). In general, SVRs can provide single or three-phase regulation in the substation bus and/or along the feeders.

2.2.1.3 Shunt capacitor

Shunt capacitors are essential to the reliable operation of distribution systems (IEEE, 2011). If properly applied, they can reduce voltage drop and losses by locally compensating inductive loads and reducing the total current from the substation to their location (SHORT, 2004). Because SCs are an economical means of supplying reactive power, they are widely used for power-factor correction and voltage control (KUNDUR, 1994; MEIER, 2006), increasing the performance of the distribution system. Local controllers are responsible for automatically switching the banks of SCs by sensing local variables (such as voltage, current, kvar, etc.) or responding to simple time clocks (DAS, 2016). In fact, these local controllers use time delays and bandwidths, similar to OLTC and SVR equipment, to automatically switch SCs (PARK; NAM; PARK, 2007).

2.2.2 SCADA-based Volt/VAr control

SCADA-based Volt/VAr control equips the system with sensors and communication facilities to remotely monitor and control the Volt/VAr devices (ULUSKI, 2011), improving

VVC effectiveness (LI et al., 2019). Based on real-time substation and field measurements, the predefined script rules, which are built in the VVC processor, determine the control actions of these devices (ULUSKI, 2010a). Independent systems control capacitor banks and voltage regulators (ULUSKI, 2010b). While the first aims to improve power factor and reduce losses, the second one gives attention to meet voltage standards and CVR purposes. Therefore, there is no integration between var dispatch and voltage control systems (RAHIMI; MARINELLI; SILVESTRO, 2012).

Strengths of SCADA-based Volt/VAr include (LI et al., 2019; ULUSKI, 2011): efficiency improvement when comparing with stand-alone controllers (traditional approach), self-monitoring, “visibility” of some remote conditions, and capability to override control actions when needed. Weaknesses of such approach include (ULUSKI, 2011; GONEN, 2014): less scalable than stand-alone controllers, more complicated due to the required extensive communication facilities, lack of adaptability (necessary to deal with feeder reconfiguration, varying operating needs, and DG penetration), and non-optimal system operation.

2.2.3 DMS-based Volt/VAr control

DMS-based Volt/VAr control is the most advanced framework to implement centralized Volt/VAr control solutions. This approach integrates several smart grid technologies and tools to carry out Volt/VAr optimization (VVO) and thereby making the distribution system operation even more efficient and reliable without compromising fundamental operating requirements (MADRIGAL; ULUSKI, 2015). The core engine of this approach is the integrated Volt/VAr control (IVVC), which runs an online power flow analysis and optimization to develop and execute a VVO switching plan (DONG et al., 2018). IVVC uses a dynamic operating model of the distribution system to reflect the current state of the network and ensure a precise Volt/VAr control (TAYLOR, 2012). That is why, this approach is also addressed as model-based VVO.

Based on real-time monitoring data from smart meters in the field (i.e., substation and along the feeders), the IVVC engine runs the optimization algorithm, which interacts with the online power flow, to determine the optimal coordination among all Volt/VAr control devices transmitting new settings to their field controllers via SCADA system (ULUSKI, 2010b). Thus, by optimizing the voltage and reactive power of the distribution network, utilities’ operating objectives can be pursued, such as (RANAMUKA; AGAL-GAONKAR; MUTTAQI, 2019): minimize power losses, increase overall system efficiency asset utilization, reduce operational cost, implement demand side management, promote energy conservation (i.e., CVR), and improve power quality and voltage stability margins.

More details about IVVC can be seen in Gonen (2014), Uluski (2010b), Uluski (2011). However, other functions and components that are worth mentioning are:

- Distribution system model is kept up to date based on information about permanent changes, dynamic changes, and temporary changes received by geographic information systems (GIS), real-time updates via SCADA, and distribution system operator, respectively (ULUSKI, 2010a);
- AMI collects data from smart meters in quasi real-time intervals (MANBACHI et al., 2017), ensuring observability of the service provided to end-use customers (DAS, 2016). In addition, a meter data management system (MDMS) can support storage, management, and processing of meter data for optimization purposes (NIYATO; WANG, 2012);
- Intelligent electronic devices (IEDs) for capacitor banks and voltage regulators can perform data acquisition (e.g., measurement readings and device status) and respond to remote control commands by executing tap changes (SALVADORI et al., 2013; MADRIGAL; ULUSKI, 2015). Thus, they intermediate the communication between control devices and VVO engine. In the substation, the remote terminal unit (RTU) serves as a data concentrator, being an interface between SCADA system and substation IEDs (WESTER et al., 2015).

Strengths of DMS-based Volt/VAr control include (LI et al., 2019; MCGRANAGHAN; ULUSKI, 2011; ULUSKI, 2010b): coordinated and optimal solution, flexible operating objectives, ability to handle complex feeder arrangements, and capable to handle high penetration of DERs (IVVC can model their dynamic effects and further control them as part of the VVO strategy). Weaknesses of such approach are mainly related to the high cost of implementation, operation, and maintenance (RAHIMI; MARINELLI; SILVESTRO, 2012), but it is possible to reduce ownership costs through shared infrastructure and resources of modern distribution systems (TAYLOR, 2012).

As an additional advantage, DMS-based Volt/VAr control fulfills the requirements for real-time implementation presented in Mello, Pfitscher and Bernardon (2017) which includes: 1) three-phase unbalanced power flow to optimize and validate the operation; 2) centralized control system with DMS and support for SCADA; 3) real-time data record of the AMI in the field equipment; 4) remotely controllable devices with commutable controllers; and 5) efficient and modern communication system.

2.3 Optimal Volt/VAr control

2.3.1 From traditional to optimal Volt/VAr control

Traditional Volt/VAr controls, based on local automatic controls, are able to perform well the basic objectives. They try to reach good results just by making compromises in the choice of controllers settings, their bandwidth and time delays (ROYTELMAN; WEE;

[LUGTU, 1995](#)). However, they present some limitations related to the lack of coordination among devices (one may initiate control actions that counteract or oscillate another device), the lack of optimal solutions under all operating conditions, and the lack of flexibility to respond to changing conditions (system reconfiguration, DGs penetration, etc.).

Rule-based controls have some efficiency improvement when compared to traditional ones. Because they present a remote monitoring capability, strategic locations can be monitored and controlled by incorporating their measurements into the control logic of the rules. However, the control outcome is not necessarily the optimal (or near-optimal) under all conditions due to the lack of coordination among the devices. Moreover, fixed script rules do not adapt to the dynamic behavior of the system, which can lead to reduced performance when faced with changing feeder reconfiguration, varying operational needs, and DG penetration. Thus, rule-based controls end up having the same weaknesses, but not in the same extension, as the local automatic controls.

On the other hand, IVVC offers a complete solution for Volt/VAr control dealing with the limitations presented by the other approaches. IVVC is a fully coordinated control that provides optimal operations for the network. It makes use of the available real-time measurements and a dynamic operating model of the distribution system to feed a real-time power flow. This means that, the current operating configuration of the system are indeed considered, covering switching status of the Volt/VAr devices, feeder arrangements and status of the system components. Of course, feedback voltage and load data information make consistent the control operation. Moreover, the effects of distributed energy resources and modern grid elements (e.g., expansions in electric vehicle charging infrastructure) can be modeled for a coordinated operation of the network. Thus, maximum performance benefits can be achieved in a smart grid context by reducing demand and energy, real power losses and operating costs, while voltage quality is ensured.

2.3.2 Open issues on the optimal Volt/VAr control

Recently, CVR has gained an increasing interest in modern distribution systems due to its attractive energy-saving capacity and the new infrastructure deployed across networks ([GUTIERREZ-LAGOS; OCHOA, 2019](#)). Even though it is not a new concept, CVR applications have evolved in pace with modern VVC solutions. As DMS model-based VVC technologies have been continuously adopted ([RANAMUKA; AGALGAONKAR; MUTTAQI, 2019](#)), paving the way for advanced CVR solutions, great attention is now focused on finding cost-effective optimization solutions for optimal operation of the grids ([MANBACHI et al., 2016b](#)).

The mathematical model of the VVO results in a mixed integer non-linear programming (MINLP) that includes discrete and continuous control variables and involves nonlinear power flow equations for a three-phase unbalanced distribution feeder. MINLP

problems are NP hard and difficult to solve for a large number of constraints ([JOTHIBASU; DUBEY; SANTOSO, 2019](#)). In general, to reduce complexity and enable scalability, methods have been proposed to relax the MINLP problem, when modeling the VVO-based CVR, into mixed-integer linear program (MILP) and nonlinear programming (NLP) sub-problems to be solved by classical optimization within reasonable amount of time ([JHA et al., 2019](#); [PAASO; LIAO; CRAMER, 2014](#)). However, linear approximations and relaxation techniques present drawbacks to capture losses, guarantee feasible solutions, and deal with integer variables ([JOTHIBASU; DUBEY; SANTOSO, 2019](#)). In addition, with the advent of efficient commercial solvers based on mathematical optimization, the problem turns out to be the development of complex and realistic mathematical models and not the development of the solution method ([ANTUNEZ, 2018](#)).

On the other hand, evolutionary algorithms (EAs) have ability for solving black box optimization problems, which permit to work with simulation tools, and dealing with non-linear and non-convex search space ([NOMAN; IBA, 2016](#)). Thus, the focus of the VVO-based CVR becomes the integration between solution method and realistic models. Furthermore, evolutionary multi-objective optimization (EMO) can capture more than one utility-specific goals, which usually are conflicting objectives, to cover the overall performance of the distribution system operation. Although the VVO-based CVR has been solved by EMO algorithms ([PADILHA-FELTRIN; RODEZNO; MANTOVANI, 2015](#); [SINGH et al., 2020](#); [XU et al., 2019](#)), there is a lack of studies that consider the CVR benefits together with efficient tap change operations of Volt/VAr devices in a multi-objective optimization problem (MOP) structure. If, in order to keep the voltage levels in the allowable lower limits, the solution requires an excessive number of tap changes, this would mean an inefficient asset utilization and a more expensive system operation, invalidating the benefits that energy savings could provide. Conventional strategies handle with the number of tap changes by considering them into the constraints of the MOP ([SINGH et al., 2020](#); [XU et al., 2019](#)). But further investigation is necessary to assess the impact of the tap-changing on the CVR and propose effective decision support to distribution system's operator.

Another issue that can arise due to the procedure of maintaining voltages at the allowable lower limits is that dynamic changes in the variables of the system operation may influence the feasibility of the CVR solution. In other words, voltage reduction can produce under-voltage violations at changing system conditions, driven by uncertainty of consumers behavior and DG availability. Although the optimal operation of CVR has been widely explored in the literature ([GUTIERREZ-LAGOS; OCHOA, 2019](#)), the authors in [Quijano and Padilha-Feltrin \(2019\)](#) pointed out that until that moment no studies in the literature had considered the implementation of CVR during the operation planning stage (optimal day-ahead operation scheduling), taking into account DG generation uncertainties. Thus, the authors themselves have dealt with this problem and, more recently, new methods

have emerged to consider the uncertainties of load and DERs within the CVR design (SINGH et al., 2018; SINGH; PAMSHETTI; SINGH, 2019; SINGH et al., 2020). But the problem of incorporating efficient tap-changing into the CVR design in the presence of uncertainties remains open to be solved by EMO algorithms.

In general, stochastic optimization (SO) and robust optimization (RO) are the two major methods widely applied to handle with uncertainties (XU, 2019). Recent works have employed these methods to schedule the VVC devices together with DERs — SO was applied in Singh et al. (2018), Singh, Pamshetti and Singh (2019) and RO in Gao, Liu and Wang (2018), Zhang et al. (2019). The main purpose is to obtain a full coordination so that performance improvement could be achieved in the presence of uncertainties, leaving the task of dealing with sudden realizations of these uncertainties to the fast-acting devices, like the smart inverters. However, this thesis has identified key research gaps in this existing state-of-art. Multi-objective robust evolutionary optimization methods have not been reported in the literature to solve the VVO-based CVR. Denoted by multi-objective robustness optimization in Paenke, Branke and Jin (2006), these approaches consist in finding a trade-off between nominal performance and robustness measure (BRANKE; LU, 2015), that is, a balance between optimality and robustness. So, they can suggest designing CVR solutions that maximize both energy savings and robustness at the same time. Moreover, there is a lack of robust metrics to evaluate how robust is a VVO solution when dealing with uncertainties and a lack of studies to estimate the costs associated with increasing such robustness.

Additionally, there is a trend towards using DERs as control variables, even more after the new IEEE 1547-2018 standard (IEEE, 2018), which allows the use of their capability of supplying reactive power with the perspective of further voltage regulation and Volt/VAr control (ALBUNASHEE; CANN, 2019). However, the authors in Zhang et al. (2020) inquired whether the conventional Volt/VAr devices (like SCs) are efficient to answer the challenges associated with highly stochastic PV power generation, remaining an open question. So, this thesis attempts to respond this query by using only conventional Volt/VAr devices, not depending on fast-acting devices (e.g., smart inverters), which may not be available in the system or whose control may be limited by standards — e.g., the difficult task of coordinating control under high DG penetration is leading utilities to have more stringent grid connection requirements (SUN et al., 2019) — and, in addition, they could mask the ability of the solving method to handle discrete variables.

2.4 Concluding remarks

This chapter has given an overview of the Volt/VAr control as a determining function to improve energy efficiency and quality in distribution networks. Remarkably, the optimization approach has received the greatest attention due to its potentialities to

further enhance system operation objectives.

In the grid modernization initiatives, the deployment of new infrastructure and technologies are followed by the implementation of updated distribution operations ([AGUERO; KHODAEI, 2018](#)), in which the Volt/VAr control is included. Therefore, IVVC should become much more effective than traditional approaches ([PADILHA-FELTRIN; RODEZNO; MANTOVANI, 2015](#)). Therefore, the methods proposed in this thesis rely on this platform that offers all resources to implement advanced Volt/VAr control strategies from a multi-objective optimization perspective.

This thesis attempts to propose new solutions in order to fulfill the research gaps highlighted in [subsection 2.3.2](#). Furthermore, the literature review extends throughout this thesis, detailing what is lacking in the literature and what has been done in the present research to contribute to the state-of-the-art in Volt/VAr control. In summary, efforts are made towards EMO algorithms to efficiently solve multi-objective VVO problems modeled by integrating CVR goals, efficient tap-changing, and robustness (to face load/DG uncertainties) in view of cost-effective solutions for real-time scale applications with decision-making support.

3 EVOLUTIONARY MULTI-OBJECTIVE OPTIMIZATION

Many real-world optimization problems require to optimize two or more objectives at the same time. That is why they are known as multi-objective optimization problems (MOPs), being a very important research topic. Normally, MOPs present conflicting objectives, the optimal solution for one objective may not be optimal for the others. So, if one objective is neglected in the optimization, relevant information for the decision maker may be lost, producing inconsistent results. In addition, there might be constraints imposed on the objectives.

Most MOPs do not have a single solution, but a set of solutions which are trade-offs (or good compromises) among the objectives (COELLO, 2006). This set is called Pareto optimal set. Each solution of this set is a Pareto optimum, i.e., there is no other feasible solution which increases some objective without causing a simultaneous decrease in at least one other objective. In other words, the vectors representing the solutions of this set are nondominated. The resulting plot of the nondominated solutions in the objective space is called Pareto front, which is the main outcome to be obtained in multi-objective optimization (NEBRO et al., 2008).

Generally, solving MOPs is a very difficult goal. In an attempt to stochastically solve these problems in an acceptable timeframe, a class of multi-objective evolutionary algorithms (MOEAs) have been developed (VELDHUIZEN; LAMONT, 2000). Computer-based evolutionary processes can be used as efficient way to solve optimization problems and handle constraints. In this context, MOEAs exploit the search capabilities of the evolutionary algorithms (EAs) to solve MOPs.

Evolutionary algorithms are capable of dealing simultaneously with a set of possible solutions. This allows to find an entire set of Pareto optimal solutions in a single run, differently from the traditional techniques (mathematical programming techniques) that perform a series of separate runs. Moreover, EAs are less susceptible to the shape or continuity of the Pareto front (e.g., they can easily deal with discontinuous and concave Pareto fronts), which are a real concern for traditional techniques (COELLO, 1999; COELLO, 2006).

It is important to mention that the term evolutionary algorithm refers to a general class of algorithms based on the principles of evolution and heredity. Such algorithms maintain a population of potential solutions and have some process of selection based on individuals' fitness and some genetic or bio-inspired operators (MICHALEWICZ, 1996). EA is a flourishing field of research that goes much wider than the original genetic algorithm (GA) and covers the developments of several years (REEVES, 2003).

This chapter gives an overview of the multi-objective optimization theory. The concepts are given in the form of definitions like the referenced materials. Then, reasons for using EAs are highlighted to encourage their use in solving the VVMO problems. Without loss of generality, the following sections take into account minimization problems for all objectives.

3.1 Single-objective optimization problem

This section presents the formal formulation of single-objective optimization problems in the form of definitions, as can be seen in (COELLO; LAMONT; VELDHUIZEN, 2007).

3.1.1 General problem

Definition 1: A general single-objective optimization problem is defined as

$$\begin{aligned} &\text{minimize} && f(\vec{x}) \\ &\text{subject to} && g_i(\vec{x}) \leq 0, \quad i = 1, \dots, m, \\ &&& h_j(\vec{x}) = 0, \quad j = 1, \dots, p, \end{aligned} \tag{3.1}$$

where $\vec{x} = [x_1, \dots, x_n]^T$ is a n -dimensional decision variable vector from the universe Ω , which contains all possible $\vec{x}$ that can be used to satisfy an evaluation of $f(\vec{x})$ and its constraints.

A solution that minimizes the scalar $f(\vec{x})$ must simultaneously satisfy the constraint functions $g_i(\vec{x})$ and $h_i(\vec{x})$ in order to be a feasible solution.

3.1.2 Global minimum optimization

Definition 2: Given a function $f : \Omega_f \subset \Omega \subseteq \Re^n \rightarrow \Re$, where $\Omega_f \neq \emptyset$ and $\vec{x} \in \Omega_f$, the value $f^* \equiv f(\vec{x}^*) > -\infty$ is called a global minimum if and only if

$$\forall \vec{x} \in \Omega_f : f(\vec{x}^*) \leq f(\vec{x}) \tag{3.2}$$

where $\vec{x}^*$ is by definition the global minimum solution, f is the objective function, and Ω_f is the feasible region of $\vec{x}$.

3.2 Multi-objective optimization problem

Now, this section presents the formal formulation of the MOPs using definitions, as presented in Coello, Lamont and Veldhuizen (2007), Deb (2001), Sierra and Coello (2006), to lay down the basic terminology, concepts, set of symbols and formal relationships.

3.2.1 General problem

Definition 3: A general multi-objective optimization problem is defined as

$$\begin{aligned}
 &\text{minimize} && \vec{F}(\vec{x}) = [f_1(\vec{x}), \dots, f_k(\vec{x})] \\
 &\text{subject to} && g_i(\vec{x}) \leq 0, \quad i = 1, \dots, m, \\
 &&& h_j(\vec{x}) = 0, \quad j = 1, \dots, p,
 \end{aligned} \tag{3.3}$$

where $\vec{x} = [x_1, \dots, x_n]^T$ is a n -dimensional decision variable vector from the universe Ω , which contains all possible $\vec{x}$ that can be used to satisfy an evaluation of $\vec{F}(\vec{x})$.

A solution that minimizes the components of the vector $\vec{F}(\vec{x})$ must simultaneously satisfy the constraint functions $g_i(\vec{x})$ and $h_i(\vec{x})$ in order to be a feasible solution. This definition extends the single objective formulation to reflect the many objectives in the MOPs. Accordingly, there is not one unique solution but a set of solutions, in a multi-dimensional space, for the decision maker to choose.

Basically, the n decision variables are numerical quantities assigned in the vector $\vec{x}$ that can be controlled within the decision space Ω — the n -dimensional space of the decision variables. Variable bounds restrict each decision variable x_i within a lower x_i^L and an upper x_i^U bounds as $x_i^L \leq x_i \leq x_i^U$. These bounds form the decision space Ω .

The evaluation of the decision vector $\vec{x}$ through k objective functions $[f_1(\vec{x}), \dots, f_k(\vec{x})]$ measures attributes of the problem, giving a quality of this solution in terms of an objective vector $\vec{y} = [y_1, \dots, y_k]$ plotted in the objective space Λ — the k -dimensional space of the objective functions. Every point in the decision space represents a solution and it gives a certain associated point in the objective space. In other words, it is a mapping from the vector of decision variables $\vec{x}$ to output vectors $\vec{F}(\vec{x})$, represented by the evaluation function $\vec{F} : \Omega \rightarrow \Lambda$.

The $m + p$ constraint functions refer to the restrictions involved in the problem that must be satisfied in order to consider a certain solution feasible. On the other hand, a solution that does not satisfy all constraints is called infeasible. So, in the presence of such constraints, the decision space Ω may not be entirely feasible. The set of all feasible solutions is called the feasible region, Ω_f . In summary, the goal of MOP is to optimize simultaneously the k objective functions and, at the same time, satisfy the constraints.

According to the nature of the problem, the vector of decision variables can be continuous or discrete as well as the objective functions. Furthermore, objective functions can be linear or nonlinear.

3.2.2 Concept of dominance

Definition 4: Given two vectors $\vec{u}$ and $\vec{v} \in \Omega$, where $\Omega \subseteq \mathfrak{R}^n$, it is said that $\vec{u}$ dominates $\vec{v}$ (denoted by $\vec{u} \prec \vec{v}$), if and only if $\vec{F}(\vec{u}) \prec \vec{F}(\vec{v})$, i.e., $\forall i \in \{1, \dots, k\}, f_i(\vec{u}) \leq f_i(\vec{v}) \wedge \exists i \in \{1, \dots, k\} : f_i(\vec{u}) < f_i(\vec{v})$.

Alternatively, it is said that $\vec{u}$ dominates $\vec{v}$ (denoted by $\vec{u} \prec \vec{v}$) if $\vec{F}(\vec{u}) \prec \vec{F}(\vec{v})$, i.e., $f_i(\vec{u}) \leq f_i(\vec{v})$ for $i = 1, \dots, k$, and $\vec{F}(\vec{u}) \neq \vec{F}(\vec{v})$.

In the multi-objective optimization, Pareto dominance is the key role for comparing vectors. According to the definition, $\vec{u}$ dominates $\vec{v}$ if $\vec{u}$ is better than $\vec{v}$ for at least one objective f_i and is not worse for any other. Then, candidate solutions can be compared to each other to decide which solution is better in terms of the objectives. Figure 1 shows three situations that $\vec{u}$ dominates $\vec{v}$ for a two-objective optimization problem. Generally, to assist visually in identifying Pareto dominance, a sketch, similarly to a cone, is drawn with parallel lines to the coordinate axes starting from a point under analysis $\vec{F}(\vec{u})$. Every one of the other points located in the cone with vertex in $\vec{F}(\vec{u})$ has its pre-image (i.e., its corresponding vector in the decision space) dominated by $\vec{u}$.

Figure 1: Three situations that $\vec{u}$ dominates $\vec{v}$ for a two-objective optimization problem

It is important to note that three situations can happen as result of the domination check when comparing two solutions $\vec{u}$ and $\vec{v}$:

- $\vec{u} \prec \vec{v}$ ($\vec{u}$ dominates $\vec{v}$);
- $\vec{v} \prec \vec{u}$ ($\vec{v}$ dominates $\vec{u}$);
- $\vec{u} \not\prec \vec{v} \wedge \vec{v} \not\prec \vec{u}$ (they do not dominate each other).

Also, there are some important properties of the dominance to be mentioned. They are:

- not reflexive: any solution $\vec{u}$ does not dominate itself;
- asymmetric: if $\vec{u} \prec \vec{v}$, then $\vec{v} \not\prec \vec{u}$. But, if $\vec{u} \not\prec \vec{v}$, this does not imply that $\vec{v} \prec \vec{u}$;
- transitive: if $\vec{u} \prec \vec{v}$ and $\vec{v} \prec \vec{w}$, then $\vec{u} \prec \vec{w}$.

Definition 5: It is said that a vector of decision variables $\vec{u} \in \Omega \subseteq \Re^n$ is nondominated with respect to Ω , if there does not exist another $\vec{v} \in \Omega$ such that $\vec{F}(\vec{v}) \prec \vec{F}(\vec{u})$.

3.2.3 Pareto optimality

Definition 6: Given a vector of decision variables $\vec{u}^* \in \Omega_f \subset \Omega$, where $\Omega \subseteq \Re^n$ and Ω_f is the feasible region, it is said that $\vec{u}^*$ is Pareto-optimal if it is nondominated with respect to Ω_f .

The Definition 6 completes the Definition 5 stating that if a decision variable vector is nondominated with respect to the entire feasible region, then it is a Pareto-optimal solution. Figure 2 illustrates both definitions. Although the vector $\vec{y}_4$ is nondominated with respect to Ω , it is an infeasible solution when all constraints are taken into account. On the other hand, $\vec{y}_2$ is nondominated regarding the feasible region Ω_f . Therefore, it is a Pareto-optimal solution.

Figure 2: Nondominated solution and Pareto-optimal solution

Definition 7: For a given MOP, the Pareto-optimal set $\mathcal{P}^*$ is defined as

$$\mathcal{P}^* := \{\vec{x} \in \Omega_f \mid \neg \exists \vec{x}' \in \Omega_f : \vec{F}(\vec{x}') \prec \vec{F}(\vec{x})\}, \quad (3.4)$$

or alternatively,

$$\mathcal{P}^* := \{\vec{x} \in \Omega_f \mid \vec{x} \text{ is Pareto-optimal}\}. \quad (3.5)$$

Pareto-optimal set is composed by Pareto-optimal solutions, whose components cannot be all simultaneously improved. These solutions do not dominate each other and they are also known as non-inferior, admissible, or efficient solutions. Their corresponding vectors are nondominated.

The solutions of the Pareto-optimal set are better compared to the rest of solutions. They collectively dominate all other solutions which do not belong to this set.

Definition 8: For a given MOP and the Pareto optimal set $\mathcal{P}^*$, the Pareto front $\mathcal{PF}^*$ is defined as:

$$\mathcal{PF}^* := \{\vec{F}(\vec{x}) \mid \vec{x} \in \mathcal{P}^*\}. \quad (3.6)$$

Pareto front is a collective plotting of the nondominated vectors in the objective space, i.e., it is the image of the Pareto-optimal set. MOPs may have uncountable set of solutions on the Pareto front. These solutions are trade-offs among the objectives, representing compromises that best satisfy the objective functions together. Thus, the decision maker may select one solution with acceptable performance of the overall objectives.

Figure 3 illustrates the Pareto front $\mathcal{PF}^* \subset \Lambda_f$ resulted from the minimization of a two-objective optimization problem. Several points are sampled in the Pareto front, which is represented by the continuous line, as well as nondominated points in the feasible region.

Figure 3: Pareto front for a two-objective optimization problem

In practice, not all the Pareto optimal set is normally desirable or achievable (COELLO, 2011). For many problems, especially for combinatorial optimization problems, proof of optimality is a computationally infeasible solution (KONAK; COIT; SMITH, 2006). Therefore, a practical approach for MOP is to investigate a set of solutions that approximate to the Pareto optimal set as close as possible (the *best-known* Pareto set). In fact, near-optimal solutions are often enough for real-world problems.

So, throughout this thesis, the Pareto front will refer to the best-known (near-optimal) solutions in the objective space, while the *true* Pareto front to the optimal

solutions. Also, the pre-image of the Pareto front will be termed simply by Pareto set (or nondominated set).

3.2.4 Constrained dominance

A simple extension to the definition of dominance was proposed by Coello and Pulido (2001), Deb et al. (2002), Coello and Pulido (2005) in order to deal with constraints. When comparing two vectors in the presence of constraints, there may be three situations: both vectors are feasible, one is feasible and other is not, and both are infeasible.

Definition 9: Given two vectors $\vec{u}$ and $\vec{v} \in \Omega$, where $\Omega \subseteq \mathbb{R}^n$, it is said that $\vec{u}$ constrained-dominates $\vec{v}$ (denoted by $\vec{u} \prec_c \vec{v}$), if any of the following conditions is true:

- a) $\vec{u}$ is feasible and $\vec{v}$ is not;
- b) both are infeasible, but $\vec{u}$ has a small overall constraint violation;
- c) both are feasible, but $\vec{u}$ dominates $\vec{v}$ ($\vec{u} \prec \vec{v}$).

3.3 Multi-objective optimization methods

According to Deb (2001), at least two classes of methods have been used to solve MOPs: classical methods and evolutionary methods. As one of the objectives of this thesis is to optimize the Volt/VAr control in a multi-objective way, the methods commonly used for such problems will be introduced in this section.

3.3.1 Classical methods

Classically, MOPs are often solved employing techniques that aggregate the objective functions (or reformulate them as constraints). By using different weights of the aggregated function (or parameters of the constraints), it is possible to obtain different points on the Pareto front (EMMERICH; DEUTZ, 2018).

3.3.1.1 Weighted sum approach

This method transforms the multi-objective optimization problem into a scalar optimization problem (COELLO, 1999). Also known as aggregating functions, the objective functions are added together using weighting coefficients in the following form:

$$\min \sum_{i=1}^k \omega_i f_i(\vec{x}) \quad (3.7)$$

where ω_i are the weighting coefficients, $\vec{x} = [x_1, x_2, \dots, x_n]^T$ is the vector of decision variables, and $f_i : \mathbb{R}^N \rightarrow \mathbb{R}, i = 1, 2, \dots, k$ are the objective functions.

The weights give a relative importance to the objectives, which means that the results vary as the weights change. So, it may be difficult to choose properly these

coefficients, requiring many simulations for their determination. Indeed, many different values of w_i locate points in the Pareto set, but concave portions cannot be found for non-convex search spaces.

This approach is the most intuitive one to deal with multiple objectives. Basic mechanisms of meta-heuristic algorithms can be applied directly without any modification. Therefore, weighted sum approach is very simple, easy to implement and efficient, working properly for problems with few objectives and convex search spaces (COELLO, 2001).

3.3.1.2 ϵ -constraint method

In this method, one of the objective functions — the most relevant or preferred — is minimized while the others are treated as additional constraints limited by some allowable levels ϵ_j . Then, these levels ϵ_j are altered to generate the entire Pareto optima set. The following formulation expresses this method:

$$\text{minimize } f_i(\vec{x}), \quad i \in (1, \dots, k) \quad (3.8a)$$

$$\text{subject to } f_j(\vec{x}) \leq \epsilon_j, \quad j = 1, \dots, k \text{ and } j \neq i. \quad (3.8b)$$

Adequate values for ϵ_j can be identified by carrying out independent single-objective optimizations for each objective in a preliminary analysis (COELLO, 1999).

This method is characterized by the trade-off concept of trading a value of one objective function for a value of another function and, although relatively simple, it is a time-consuming technique (COELLO; LAMONT; VELDHUIZEN, 2007).

3.3.2 Multi-objective evolutionary algorithms

The class of evolutionary algorithms is able to solve problems involving multiple conflicting objectives and intractably large and highly complex search spaces (ZITZLER; LAUMANN; BLEULER, 2004). So, the main purpose of this section is to present general characteristics of the multi-objective evolutionary algorithms and to explore reasons for use of EAs. Specific details on how to implement standard EAs can be found in the references throughout the thesis.

3.3.2.1 General characteristics

Evolutionary algorithms applied in solving multi-objective optimization problems are called multi-objective evolutionary algorithms (MOEAs) and, in general, the field is known as evolutionary multi-objective optimization (EMO). These terms are used indistinctly. According to Coello, Lamont and Veldhuizen (2007), the primary goals for a MOEA are:

- a) preserve nondominated points in the objective space and their corresponding points in the decision space;
- b) make the optimization progress continuously towards the Pareto Front in the objective space;
- c) maintain diversity of points on Pareto front;
- d) provide to the decision maker enough, but limited, number of Pareto points for selection of the decision variable vector values.

Evolutionary algorithms have been highly employed to solve multi-objective problems. For this purpose, MOEAs extend a traditional EA in the following main aspects (COELLO, 2011):

- a) selection mechanism: the aim of MOEAs is to select nondominated solutions and not the solutions with the highest fitness. Normally, all the nondominated solutions in a population are considered as equally good;
- b) diversity maintenance: MOEAs require a mechanism that preserves diversity and avoids convergence to a single solution. The main idea is to favor the exploration of regions of search space in which there are less solutions;
- c) elitism: it is a mechanism employed to guarantee convergence and normally consists of using an external archive that can (or cannot) interact in different ways with the main population. This archive stores all nondominated solutions generated throughout the search process, removing those that become dominated later in the search. Thus, the final contents of this archive represent an approximation of the Pareto optimal set.

3.3.2.2 Reasons for EAs to solve Volt/VAr MOPs

Essentially, the success of the Volt/VAr control depends on the proper coordination among the equipment. Different equipment settings will result in different performances of the system. So, it is possible to pursue optimal results by modeling the Volt/VAr control as an optimization problem. In addition, when more than one utility-specific goals is desired, a multi-objective optimization problem can be taken into account so that the overall efficiency of the distribution system can be improved. Therefore, Volt/VAr control fits very well for optimization problems. Some other reasons are (VITOR; ASADA; VIEIRA, 2020):

- a) objective functions can represent utility goals;
- b) essential limitations and requirements of the operation can be modeled as constraints;
- c) voltage regulating equipment and reactive controls can be handled as the control variables;

- d) objective functions can be evaluated by algorithms or simulation tools;
- e) flexibility of modeling the operating objectives and constraints;
- f) the control variables can be encoded as continuous or discrete;
- g) different techniques can be used to solve the problem;
- h) trial and error adjusts are avoided;
- i) in-depth knowledge of the system is not necessary (depend on the optimization technique);
- j) efficient algorithms can be designed to solve the problem for real-time applications;
- k) system optimization is part of the smart grid strategy.

However, MOPs may present some difficulties due to the complexity involved, such as: multiple conflicting objectives, intractable large and highly complex search spaces, and uncertainty ([ZITZLER; LAUMANN; BLEULER, 2004](#); [COELLO; LAMONT; VELDHUIZEN, 2007](#)). As drawbacks may accompany classical methods to solve these problems ([ZITZLER, 1999](#); [DEB, 2001](#)), EAs can be used, since they present several characteristics to deal with the above-mentioned difficulties ([DEB, 2001](#)), outperforming the classic methods on real problems ([FOGEL, 2007](#); [NOMAN; IBA, 2016](#)).

Evolutionary algorithms have a population-based nature that enables them to find multiple optimal solutions in a single run, facilitating the solution of multi-objective optimization problems ([DEB, 2011](#)). They also present some characteristics that contribute to their robustness, such as: direct use of coding, blindness to auxiliary information, randomized operators, scalability, and capability of working with noisy search spaces and imperfect models ([NOMAN; IBA, 2016](#); [GOLDBERG, 1989](#)). Finally, due to the ability of EAs to deal with a “black box optimization problem” (i.e., they only require coding and performance measure of the problem due to a set of actions), simulators of power distribution systems can be used to provide an integrated solution for optimal Volt/VAR control.

3.4 Concluding remarks

This chapter has laid theoretical foundations of the multi-objective problem so that, in the following chapters, the Volt/VAR control may be modeled in this manner. The advantages of this formulation rely on the capability of improving the overall operation efficiency of distribution systems by dealing with conflicting objectives and providing a set of trade-off solutions. Thus, the distribution operator might choose a reasonable solution according to its policies.

Several reasons have been presented encouraging this thesis to use EAs. Accordingly, the following chapters will present proposals based on EAs to solve the VVMO problems.

In summary, the purpose of this chapter was to present various algorithmic concepts, definitions and motivations. Further details and in-depth analysis are made along with the development of the forward chapters.

4 SPECIALIZED EVOLUTIONARY SYSTEM FOR VOLT/VAR MULTI-OBJECTIVE OPTIMIZATION

This chapter presents a new specialized evolutionary system for Volt/VAr optimization (SES-VVO) to efficiently solve the multi-objective problem (MOP) when the number of tap-changing operations of voltage regulating devices is considered together with the conservation voltage reduction (CVR) goals. This problem is a challenging task for evolutionary algorithms (EAs) in terms of meeting voltage limits constraints and reaching near optimal solutions. The proposed mathematical model allowed the development of specialized search mechanisms, which contributed to improve the overall performance of the day-ahead operation planning and the hourly decision-making approaches, giving more realistic and cost saving solutions for distribution systems' operators. Simulations on the IEEE 34-bus system were carried out in the presence of photovoltaic (PV) generation. Comparisons with other methods were conducted to clarify the effectiveness of the proposed method. The SES-VVO corroborated with the development of an advanced strategy that has potential for real-time operation considering the variation of load demand and the intermittence of PV generation, which were modeled by using Monte Carlo simulations. Finally, it was demonstrated that the tap change costs of voltage regulating devices have a decisive impact on the economic operation of the SES-VVO when the CVR goals are pursued by the SES-VVO approach proposed in this chapter.

4.1 Introduction

Volt/VAr optimization methods have the challenge of keeping the optimality of the operation in view of the variability of loads and intermittence of DERs. These time-varying characteristics lead to technical and economic issues concerning the number of control actions performed by the voltage regulating devices, which may operate excessively. A minimized number of tap changes must be taken into account in order to preserve the service life of these devices (YILMAZ; EL-SHATSHAT, 2018; MALAKAR; GOSWAMI, 2013; KIM et al., 2013; SHIGENOBU et al., 2018; MAHZOUNI-SANI et al., 2019; SABILLON-ANTUNEZ et al., 2017; SINGH et al., 2020; JIN; CHIANG; LI, 2019), reduce maintenance (MAHZOUNI-SANI et al., 2019), depreciation (MALAKAR; GOSWAMI, 2013) and operating costs (PAMSHETTI; SINGH, 2019; MANBACHI et al., 2016a; YILMAZ; EL-SHATSHAT, 2018), and prevent poor asset management and power quality deterioration (KIM et al., 2013). Conventional VVO formulations consider the maximum number of tap changes as a constraint (SABILLON-ANTUNEZ et al., 2017; SINGH et al., 2020), although they do not guarantee minimal tap-changing actions. Alternatively, the number of tap-changing operations are taken as an objective function to be minimized in conjunction with other objectives on a weighted sum approach (MALAKAR; GOSWAMI, 2013; KIM

et al., 2013). However, converting a multi-objective problem (MOP) into a single-objective optimization problem (SOP) has some drawbacks related to the process of determining appropriate weight coefficients, scaling of the objectives and coping with non-convex problems (CHIANDUSSI et al., 2012). Other methods for dealing with tap-changing actions follow the same principle of converting MOP into SOP (e.g., ϵ -constraint (PAMSHETTI; SINGH, 2019)) and turn out to be a weighted sum approach as well (e.g., penalties strategy (MALAKAR; GOSWAMI, 2013), fuzzification technique (MANBACHI et al., 2016b), and global criterium method (MAHZOUNI-SANI et al., 2019)).

Very few research papers have studied the minimization of tap-changing operations in MOP to be solved by evolutionary multi-objective optimization (EMO) algorithms. In Yilmaz and El-Shatshat (2018), the nondominated sorting genetic algorithm II (NSGA-II) was applied to minimize both the active power losses and the costs of operating the control devices when the system is operating normally (all critical bus voltages are within acceptable range). If bus voltages fall into other ranges, different methods are applied to bring the system back to a normal state. But, to make the solution feasible, the minimization of the costs of operating the control devices is no longer regarded as an objective. The stochastic nature of wind-based DGs was considered, but only to build three scenarios, which were solved independently without considering their effects when happening during the system operation. The authors in Shigenobu et al. (2018) proposed a method to minimize both the voltage deviations and the number of tap changes to maintain diversity of operation, and simultaneously the same method determines the optimal placement of voltage control devices. For this, they included into the NSGA-II a linkage concept that updates the fronts according to individuals' placement information. However, they did not consider uncertainties of load demand and DG in the studies. Also, the method did not present specific strategy to deal with feasibility, since the Pareto solutions were constituted not only by feasible solutions. In Jin, Chiang and Li (2019), a three-step method was proposed in the first stage of a two-stage problem to minimize both the power loss and the number of control actions. In step 1, the group-based multi-objective particle swarm optimization (MOPSO) is applied to obtain the multiple near-optimal solutions. In step 2, the user selects the solution with the least number of control actions to be further improved by translating the MOP into a SOP (the power loss is the objective while the number of control actions is taken as a constraint). Then, in step 3, the interior point method is applied to solve the SOP. So, the group-based MOPSO was not efficient enough to solve the problem, since additional steps were required to further improve the solution. The stochastic nature of the renewable energy sources (RESs) are dealt with in the second stage by using the RES inverters, which provide fast reactive power every at 15 minutes to minimize the pilot-bus voltage deviation of representative scenarios. Despite the promising results, this solution depends on smart inverters with reactive power compensation capability that may not be available in the system or whose control may be

limited by standards.

The CVR problem has been solved by EMO algorithms in MOP designs. In [Padilha-Feltrin, Rodezno and Mantovani \(2015\)](#), the objective functions to be minimized were the active power intake on the system and the voltage deviation. This study focused on mitigating the problem of voltage reduction application by using the NSGA-II. Three solutions were analyzed from the Pareto results, one with maximum energy savings, other with moderate energy savings, and the last as a combination of both. But the formulation of the problem did not model the tap change counting. Also, DG was not considered neither the uncertainty of the load forecast. In [Singh et al. \(2020\)](#), the control scheme for CVR implementation was formulated in two different time scales: slow and fast. The MOPSO was used in the slow time scale, which was formulated by stochastic optimization for the planning stage, to schedule the discretized control variables based on the minimization of both the voltage deviation from expected CVR voltage and the system losses. Among the various Pareto solutions, the one with a minimum radial distance from the origin was chosen. In the fast time scale, when voltage violated the limits due to the deficit in PV system output, real-time control was implemented using adaptive Volt/VAR droop controller. However, post-optimization sensitive analysis of the planning stage solutions was not carried out, lacking the uncertainty study of the stochastic VVO optimization results. The authors in [Xu et al. \(2019\)](#) considered the minimization of three objectives: total power loss, maximal voltage collapse proximity indicator, and total power demand. The multi-objective genetic algorithm (MOGA) procedure was used to solve the problem, followed by the compromise ranking method to select solutions. Although the uncertainties in the PV output had been modeled, their effects during the system operation were not analyzed. Also, the variability of load demand was not considered in the problem. In general, all these works used base cases to validate the effectiveness of their methods, but the performance comparison with other EMO algorithms was not carried out.

The findings of this research have identified that the integration of CVR goals with efficient tap change operations has not been designed as a MOP to be solved by EMO algorithms. Moreover, when analyzing the literature survey presented above, the following research gaps on the multi-objective VVO designs could be identified:

- a) specialized mechanisms of search to improve the overall efficiency of EAs;
- b) reference metric to access the quality of the solutions;
- c) intelligent strategies that do not only depend on fast-acting devices (e.g., smart inverters) to face the load/DG uncertainties;
- d) studies about the tap-changing operations costs impacts considering the CVR strategy;
- e) comprehensive model to design the day-ahead operation planning (OP) and the

hourly decision-making (DM) approaches.

Voltage regulation is one of the key issues that may limit the integration of renewable-based distributed generation (DG) in distribution systems (MAHMUD; ZAHEDI, 2016). Besides the voltage rise at receiving end, the intermittent nature of renewable DG makes the system operation susceptible to active power fluctuations, which may cause undesired voltage violations and result in power quality issues. So, this research focuses on designing a VVO that allows the integration of DG at the maximum share of clean energy. Furthermore, Monte Carlo simulation is applied to evaluate the robustness during system operation when stochastic errors of load/DG forecast are introduced.

Within the context presented so far, this chapter proposes a new model for the Volt/VAr multi-objective optimization (VVMO) that aims to minimize the load demand and energy losses through the CVR strategy and, at the same time, to reduce the number of tap-changing operations performed by the voltage regulating devices (OLTC, SCs and SVRs). This model has a comprehensive scope to design the OP and DM approaches. The OP pursues multiple candidate solutions that schedule the devices for one day-ahead, whereas the DM seeks a user-preferred solution to be readily implemented. Moreover, a new metaheuristic optimization method based on Evolutionary Algorithm (EA) concepts is developed empowering the NSGA-II to solve efficiently the VVMO problem.

The rolling horizon model is considered to implement hourly decision-making. The authors in Xu et al. (2019), Zhang et al. (2019) applied this model with updated load/DG predictions at each rolled horizon to address the coupling constraints. Differently, the present proposal considers actual data from real-time estimation and forecasts to incorporate the time coupling of the control as an objective function into the MOP. Also, user preferences are integrated into the decision-making.

This chapter establishes the specialized evolutionary system for VVO (SES-VVO) and provides the following main contributions:

- a) a mathematical formulation that allows the development of advanced search mechanisms to meet voltage limit constraints and reach near optimal solutions;
- b) a heuristic method for restricting the search space;
- c) a repair process that effectively satisfies voltage constraints;
- d) an expert mutation operator that efficiently minimize the tap-changing operations;
- e) an expert scheme that efficiently minimize the active power intake on the system;
- f) a procedure for better covering the Pareto front promoting solution diversity;

- g) an advanced strategy for decision-making that can speed up the search for higher efficient solutions and that presents robustness to face load/DG forecast deviation;
- h) the demonstration that the tap-changing costs have a decisive impact on the economics when the CVR goals are pursued by the VVO proposed approach.

Simulations are carried out in the IEEE 34-bus system to validate the proposals, including studies of feasibility, performance, Pareto front approximation, costs, and uncertainties. The reference metric used in this chapter to access the quality of the solutions is called reference objective vector, which was computed by optimizing each objective individually, since the ideal objective vector is difficult to obtain in practice. Also, comparisons with other methods are made showing that the SES-VVO has superior performance. The advantages of the proposed method over the existing ones in literature are:

- a) *A single algorithm is capable to solve the VVMO problem*: SES-VVO does not require to subdivide the problem into various stages (or steps) to be solved by different methods, which could increase complexity and computational time;
- b) *The SES-VVO meets the above-mentioned research gaps*: SES-VVO is an updated method that shares the advantages of the class of EAs within the smart grid context to perform advanced CVR through efficient control;
- c) *Superior performance can be achieved by using conventional VVC devices*: SES-VVO does not require advanced controls (e.g., smart inverters) to find near-optimal solutions, since these controls may not be available in the system or whose control may be limited by standards.

In return, SES-VVO could require deployed systems (e.g., AMI and DMS) to implement and operate. But smart grid technologies are continually expanding (MANBACHI et al., 2016a; MANBACHI et al., 2016b), providing opportunities for the electric power utilities to perform more efficient optimization and robust control, like the proposed SES-VVO.

4.2 Problem formulation

This section presents the proposed formulation to solve the VVMO problem, which aims to perform the CVR with a reduced number of tap-changing operations.

4.2.1 Volt/VAr multi-objective optimization problem

The proposed formulation of the VVMO considers the minimization of two different objectives: the active power intake to the distribution system from the substation, f_{PI} , and the number of tap-changing operations of voltage regulating devices, f_{SO} . The minimization of the active power intake into the system is a way to pursue energy savings by voltage

reductions (PADILHA-FELTRIN; RODEZNO; MANTOVANI, 2015). The tap-changing operations count the number of actions performed by the devices (OLTC, SCs and SVRs). Both characteristics are accumulated during a period split into discrete intervals of 1 hour. The constraints are related to power balance, operating capacity of control devices, and voltage limits.

The operation of the voltage regulating devices is determined by the following formulation:

$$\text{minimize} \quad f_{PI} = \sum_{h=h_I}^{h_F} P_{in}^h = \sum_{h=h_I}^{h_F} (P_{load}^h + P_{loss}^h), \quad (4.1a)$$

$$f_{SO} = \sum_{h=h_I+1}^{h_F} \sum_{d \in \Omega_D} |T_d^h - T_d^{h-1}| \quad (4.1b)$$

$$\text{subject to} \quad P_n^h = P_{Gn}^h - P_{Ln}^h, \quad (4.1c)$$

$$Q_n^h = Q_{Gn}^h - Q_{Ln}^h + Q_c^h, \quad (4.1d)$$

$$T_{d,min} \leq T_d^h \leq T_{d,max}, \quad (4.1e)$$

$$V_{min} \leq V_n^h \leq V_{max} \quad (4.1f)$$

where the period attains the intervals $(h_I, h_{I+1}, \dots, h_F)$, P_{in}^h is the active power intake to the system at hour h , P_{load}^h is the total active load power at hour h , P_{loss}^h is the total real power loss at hour h , Ω_D is the set of all control devices of the system, T_d^h is the tap of the device d at hour h , P_n^h and Q_n^h are the active and reactive power of node n at hour h , P_{Gn}^h and Q_{Gn}^h are the active and reactive power generation of node n at hour h , P_{Ln}^h and Q_{Ln}^h are the active and reactive power load of node n at hour h , Q_c^h is the amount of reactive power injected by capacitor c at hour h , $T_{d,min}$ and $T_{d,max}$ are the tap position limits for the device d , V_n^h is the voltage of the node n at hour h , and V_{min} and V_{max} are the acceptable voltage limits. If the daily operation is considered, the period from $h_I = 1$ to $h_F = 24$ will have $N_H = 24$ h.

4.2.2 Volt/VAr multi-objective mapping

The VVMO problem is formulated as a mapping from the design space X into the objective space Y , $\vec{f}_o : X \rightarrow Y$, where $X \subset \mathbb{N}^{N_D N_H}$ comprises all possible discrete tap configurations of the N_D devices for N_H hours of operation and $Y \subset \mathbb{R}^{N_O}$ is the distribution system response represented by the trade-offs among the N_O objectives. Thus, the evaluation of the objective functions on a decision vector $\vec{x} \in X$ produces an objective vector $\vec{y} \in Y$.

The encoding for the decision vector $\vec{x}$ is showed in Equation 4.2 as a matrix. Each element represents the tap number of a specific device (columns) at a certain time (rows).

Furthermore, each row, called sub-vector $\vec{x}_{sub}^h$, has a full configuration (taps of all devices) managed by the optimization algorithm to run the power flow at hour h . In Equation 4.3, the objective vector $\vec{y} \equiv \vec{f}_o(\vec{x})$ contains the total active power intake to the system and the total switching operations.

$$\vec{x} = \begin{pmatrix} T_1^{h_I} & T_2^{h_I} & \dots & T_{N_D}^{h_I} \\ T_1^{h_I+1} & T_2^{h_I+1} & \dots & T_{N_D}^{h_I+1} \\ \vdots & \vdots & \ddots & \vdots \\ T_1^{h_F} & T_2^{h_F} & \dots & T_{N_D}^{h_F} \end{pmatrix} = \begin{pmatrix} \vec{x}_{sub}^{h_I} \\ \vec{x}_{sub}^{h_I+1} \\ \vdots \\ \vec{x}_{sub}^{h_F} \end{pmatrix} \quad (4.2)$$

$$\vec{y} = \begin{pmatrix} f_{PI} & f_{SO} \end{pmatrix} \quad (4.3)$$

4.2.3 Volt/VAr constraint mapping

For the Volt/VAr constraint subproblem, a mapping from the design space X into the constraint voltage violation space $C \subset \mathbb{N}^{N_H}$, $\vec{f}_c : X \rightarrow C$, quantifies the violations of constraint (Equation 4.1f) in the period of N_H hours. This quantification is implemented by the following equations:

$$vv_n^h = \begin{cases} 1 & V_n^h < V_{min} \text{ or } V_n^h > V_{max}, \\ 0 & \text{otherwise;} \end{cases} \quad (4.4)$$

$$f_{VV}^h = \sum_{n \in \Omega_N} vv_n^h \quad (4.5)$$

where vv_n^h computes the existence or not of voltage violation on the node n at time h , f_{VV}^h is the number of voltage violations at hour h , and Ω_N is the set of all nodes.

4.3 Multi-objective optimization technique

In this section, Pareto dominance applied to VVMO is presented, followed by an extension scheme to handle the constraints. These concepts are the basis for the comparison of individuals (candidate solutions). Herein, the main characteristics of the NSGA-II, a highly competitive and popular EMO algorithm, are presented. Some reasons that make NSGA-II very attractive are related to its simple structure, its availability, the elaborated design of its operations, its adoption in various practical applications, and its promising results on the majority of test problems (KÖPPEN; YOSHIDA, 2007).

4.3.1 Dominance criteria

Assuming only minimization problems, the following definitions (SIERRA; COELLO, 2006) will help to describe the concept of optimality applied to VVO:

Definition 10: Given two vectors $\vec{y}^1, \vec{y}^2 \in Y$, where $Y \subset \mathbb{R}^{N_O}$, it is said that $\vec{y}^1$ dominates $\vec{y}^2$ (denoted by $\vec{y}^1 \prec \vec{y}^2$) if $\vec{y}_i^1 \leq \vec{y}_i^2$ for $i = 1, \dots, N_O$, and $\vec{y}^1 \neq \vec{y}^2$.

Definition 11: A vector of decision variables $\vec{x} \in X' \subset X$, where $X \subset \mathbb{R}^{N_D N_H}$, is nondominated with respect to X' , if there is not another $\vec{x}' \in X'$ such that $\vec{F}_O(\vec{x}') \prec \vec{F}_O(\vec{x})$.

From Definition 11, if X' is the feasible region ($\mathcal{F}$), then $\vec{x} \equiv \vec{x}^*$ is a Pareto-optimal solution. The set of Pareto-optimal solutions is called Pareto-optimal set ($\mathcal{P}^*$) whose image in the objective space is named Pareto-optimal front ($\mathcal{PF}^*$).

4.3.2 Constraint handling approach

A simple extension to the definition of dominance was presented in [subsection 3.2.4](#) to deal with constraints. Such extension can be easily applied to VVMO.

4.3.3 Nondominated sorting genetic algorithm II (NSGA-II)

Based on genetic algorithms, NSGA-II applies genetic operators to produce an offspring population. Then, the individuals in the combined parent and offspring populations are sorted according to fitness and spread metrics, and the best ones are selected to create a new population. Since previous and current populations are included in the same mating pool, elitism is ensured. NSGA-II presents at least two important considerations for guiding the selection process: fast nondominated sorting approach and diversity preservation ([DEB et al., 2002](#)):

Fast-nondominated-sort: it clusters the individuals into different nondomination levels (fronts) with reduced time complexity. Each front receives a rank according to the number of solutions which dominate its elements. The first front represents the Pareto front.

Crowding-distance: it is a density-estimation metric used to distinguish solutions of the same front to maintain diversity of Pareto fronts. The crowding-distance for a solution is estimated by the perimeter of the cuboid formed by its nearest neighbors as vertices.

4.3.4 System requirements for optimal Volt/VAr control

The system requirements for VVO are composed by the centralized control with all necessary communication infrastructure. Specifically, IVVC ([subsection 2.2.3](#)) is the framework basis for implementing the proposed methods of this thesis. Like in [Rahimi, Massucco and Silvestro \(2015\)](#), the short-term load/DG forecasting feature is added to IVVC for planning activities (i.e., day-ahead scheduling). Readers are referred to [Srivastava, Pandey and Singh \(2016\)](#) for short-term forecasting methods. Thus, the simulation framework for testing and validation purposes is customized based on the Python-OpenDSS interface, providing the essential components for IVVC implementation. This framework is illustrated in [Figure 4](#) and depicted by the following components:

- a) **Short-term load/DG forecasting** is taken from literature and historical records. These load/DG data are input for the optimizing engine;
- b) **IVVC optimizing engine** is developed using Python scripts. Selecting a computationally efficient method is one of VVO's biggest challenges. That is why this thesis focuses especially on developing new VVO algorithms;
- c) **Distribution system model** is implemented as a script-based model in the OpenDSS, being considered as an updated model that fully represents the real power distribution system;
- d) **On-line power flow** is solved by OpenDSS procedures. The power flow on the distribution system model must be evaluated whenever required. From the power flow results, all information regarding objectives and constraints can be further calculated by the IVVC algorithm.

Figure 4: IVVC framework

Source: Adapted from [Uluski \(2010b\)](#), [Rahimi, Massucco and Silvestro \(2015\)](#)

It is assumed that the remaining resources and subsystems of the DMS-based Volt/VAr control ([subsection 2.2.3](#)) are fully deployed in the system to implement the IVVC. Moreover, it is noteworthy that real-time sample values from smart meters could be used to construct real-time load profiles ([MANBACHI et al., 2014](#)). So, for this kind of applications, it is considered that the IVVC optimizing engine collects active/reactive power of loads from AMI data and estimates the load profile ([MANBACHI et al., 2016b](#)).

The OpenDSS simulation tool is able to solve multi-phase unbalanced power flow for both meshed and radial systems ([EPRI, 2020](#); [BRUNO et al., 2011](#)). Its power flow solution technique is fast and useful for sequential time solutions ([DUGAN; MCDERMOTT, 2011](#)). Also, by using the COM interface, OpenDSS can be accessed from different programming languages ([MONTENEGRO; DUGAN, 2017](#)), allowing the interaction and control between optimizing engine and power flow. The network power balance equations, which are

formulated as equality constraints in the optimization problems, are satisfied by solving the power flow in OpenDSS (ANWAR et al., 2017).

4.4 Proposed Volt/VAr multi-objective method

A general methodology is proposed to enable EAs to solve efficiently the VVMO problem. Firstly, five specialized methods are proposed. Then, at the end of this section, the complete algorithm for day-ahead operation planning is presented, followed by an advanced strategy to speed it up for hourly decision making.

4.4.1 Search space restriction

The possible tap configurations for all devices can reach impractical combinatorial problems, leading to an expensive computational time to solve the problem (MOHAPATRA; BIJWE; PANIGRAHI, 2014). Thus, the search space must be restricted. A simple, but efficient, way for limiting the search space is to define for each device d its own tap boundary limits per hour h . Thus, Equation 4.1e becomes:

$$\underline{T}_d^h \leq T_d^h \leq \overline{T}_d^h \quad (4.6)$$

where $\underline{T}_d^h$ and $\overline{T}_d^h$ are the lower and upper boundary limits permitted for the tap setting of device d at hour h .

Algorithm 1 shows a pseudocode that implements a succession of random tap changing from an initial configuration to head the search for feasible solutions, regardless of the objective function. Given the daily curves of loads and the power generation curves of DG, the heuristic chooses a tap for each device and tries to change it taking a random step drawn from a random distribution. After checking if the new tap position is within the adjustment range, the algorithm runs the power flow and stores the solution in case of feasibility. This process is repeated many times (s_{max}) forming the set of solution S from which the algorithm takes the minimum and maximum tap positions for each device as its boundary limits at that time. Then, the procedure continues for the other hours within the whole period. To prevent a series of consecutive unproductive steps, a counter will determine, after a sequence of infeasible solutions, the restart from the last feasible solution or from the initial taps, by comparing with predefined parameters, n_1 and n_2 , respectively ($n_2 > n_1$ and n_1 should not be too large).

4.4.2 Repair process

When the traditional genetic operators tend to generate infeasible solutions most of the time, repair methods can be designed to turn these solutions into feasible ones (COELLO, 2002). In this section, we propose a repair process in which the offspring must

Algorithm 1 Pseudocode of the heuristic method for restricting search space

```

1: Set initial taps. Initialize counter
2: while  $s < s_{max}$  do
3:   Choose a tap and change it
4:   Check the operating range limits
5:   Run power flow
6:   if solution is feasible then
7:     Store solution in  $S$ . Reset counter
8:   else
9:     Increase counter
10:    if counter is multiple of  $n_1$  then
11:      Come back to last feasible solution
12:    end if
13:    if counter  $> n_2$  then  $\triangleright n_2 > n_1$ 
14:      Come back to initial taps. Reset counter
15:    end if
16:  end if
17: end while
18: Find  $\underline{T}_d^h$  and  $\overline{T}_d^h$  from  $S$ 

```

have a smaller number of constraint violations than that of its progenitors, or at least equal to, in order to be added into the new population. However, instead of considering the individual $\vec{x}$ as a whole, it is split into a temporal sequence of parts $\vec{x}_{sub}^h$ as presented in [subsection 4.2.2](#).

[Figure 5](#) illustrates the repair process. A new individual is created part by part, sequentially, based on the EA. After genetic operators (crossover and mutation operators) create a new part, a power flow calculation is executed. If the constraint violations ([Equation 4.5](#)) are smaller or equal than those related to its corresponding parents' parts, the current part will be hold in the new individual; otherwise, it must be discarded, and a new attempt begins. This process is repeated until each part of the new individual fulfills such a rule.

The block Compute Repair Influence is responsible for preventing excessive tries. Within it, the function f_{RI} , which decreases with the number of attempts, will narrow the search performed by the genetic operators — it decreases the crossover and mutation probabilities throughout attempts. This function is inspired by the non-uniform mutation operator ([HERRERA; LOZANO; VERDEGAY, 1998](#)), but differently, randomness is not considered. It can be written as:

$$f_{RI} = 1 - \alpha \left(1 - \frac{rc}{rc_{max}} \right)^\beta \quad (4.7)$$

where f_{RI} is the repair influence over the search, rc and rc_{max} are the repair counter and the predefined maximum repair counter, and α and β are parameters related to the shape of the curve and to the degree of dependency on the repair counter.

Figure 5: Flowchart of the repair process for dealing with constraints

4.4.3 Holding tap position (HTP)

A mutation operator, called Holding Tap Position (HTP), is proposed to enhance the search engine capacity of finding minimal tap-changing operations. This operator applies random mutation at the initial hour h_I so that diversity may be promoted, but in following hours, $h > h_I$, it tries to hold the previous tap position at the current time step in order to avoid excessive changes. Therefore, the HTP operator adjusts the tap T_d^h by:

$$T_d^h = \begin{cases} \text{random}(T_d^h, \overline{T_d^h}) & \text{if } h = h_I, \\ T_d^{h-1} & \text{if } h > h_I; \end{cases} \quad (4.8)$$

4.4.4 Temporary artificial individual (TAI)

An individual can be artificially created based on good performances of the current population and can be added temporarily in this population during the process of generating offspring. The purpose of the Temporary Artificial Individual (TAI) is to increase the efficiency of finding minimal active power intake values. To influence offspring, it must have priority rank at the stage of parent selection. TAI is created with the best parts (sub-vectors) of the entire population concerning the f_{PI} , (see Equation 4.1a). Each sub-vector of TAI is given by:

$$\vec{x}_{sub}^{TAI,h} = \arg \min f_{PI}(\vec{x}_{sub}^{i,h}), \quad \text{for } i = 1, \dots, n_{pop} \quad (4.9)$$

where $\arg \min\{\cdot\}$ function returns the sub-vector of the smallest f_{PI} at hour h and n_{pop} is the population size.

4.4.5 Covering Pareto front

The proposed procedure applies heuristics to exchange parts (sub-vectors $\vec{x}_{sub}^h$) among individuals to better cover the Pareto front (Figure 6 and Figure 7). An exchange vector ($\vec{ev}$) encoded by a binary string is generated randomly at each iteration of this procedure. Figure 6 exemplifies the exchange of corresponding parts among two parents when the exchange vector has value equal to one. This operation produces two new individuals (offspring) without computational cost relative to power flow simulation.

The procedure begins selecting randomly two parents $\vec{x}^i$ and $\vec{x}^j$, from the Pareto set $\mathcal{P}$, in which the exchange vector is applied to produce the offspring $\vec{x}^{i'}$ and $\vec{x}^{j'}$. From the mating pool $\mathcal{M}$ (parents with offspring), the nondominated offspring are stored in the auxiliary set $\mathcal{A}$. After c_{max} runs of these steps, the nondominated individuals from the union of $\mathcal{P}$ and $\mathcal{A}$ update the Pareto set $\mathcal{P}$. Fig. Figure 7 details this procedure in a flowchart. It can be applied several times until no improvement is observed.

Figure 6: New individuals produced by the exchange vector

Figure 7: Flowchart of the procedure to cover the Pareto Front

To estimate the quality of the obtained Pareto fronts, we have used the hypervolume indicator [25], a metric that measures the area/volume of the objective space dominated by an approximation set — a region between the non-dominated set of solutions and a reference point. The larger the hypervolume, the better the set of optimal solutions. The relative quality $\mathcal{Q}$ of a set of solution S , in (15), is obtained by the percentage of the hypervolume measure of the solution set of interest $\mathcal{H}_S$ in relation to a reference hypervolume $\mathcal{H}_{ref}$ [26]. By solving two independent single objective optimization problems, one that minimizes f_{PI} and another one that minimizes f_{SO} , it is possible to obtain both, a reference point and a reference hypervolume. All values are normalized to the minimum and maximum values observed on these two independent optimization problems.

$$\mathcal{Q}(\mathcal{H}_S) = \frac{\mathcal{H}_S}{\mathcal{H}_{ref}} \times 100 \quad (4.10)$$

4.4.6 Specialized evolutionary system for VVO (SES-VVO)

The above-mentioned encoding model and strategies are merged with the NSGA-II to form the SES-VVO for solving the VVMO problem. Figure 8 shows the global flowchart that connects all parts of the proposed optimization model. First, the algorithm performs the search space restriction heuristic (Algorithm 1) to create bounds for the tap positions of all devices per hour (Equation 4.6). The population P is initialized and evaluated. Then, the fast non-dominated sort and the crowding-distance procedures of the NSGA-II are computed for P . The evolution process begins by creating the TAI (Equation 4.9) and adding it to P to influence the current generation. The next step is the creation of a new population of offspring Q . Each new offspring is created from two parents selected by means of binary tournament. Because of the complexity of time-coupling, the vectors are handled part by part through the repair process (Figure 5), which increasingly pushes the offspring into the feasible region of the search space. So, the repair influence (Equation 4.7) is computed to update the probabilities of crossover (p_c) and mutation (p_m). Then, the flat crossover (Equation 4.11) and the expert mutation HTP (Equation 4.8) operators are performed to generate a part ($\vec{o}_{sub}^h$) of the offspring ($\vec{o}^h$) at the current hour h . After the evaluation of this part, the algorithm decides whether it keeps this part as a sub-vector of the new offspring or not. In case of worsening of voltage constraints in comparison with the parents, the current part is rejected, and a new attempt starts from the repair influence computation. Otherwise, this new part will be kept as a sub-vector of the new offspring and the algorithm moves on to the next hour. When this new offspring gets complete with all sub-vectors (from h_I to h_F), it is evaluated and added to Q . Then, the process of creating a new offspring begins again. Once the size of Q is complete, the normal flow of the NSGA-II takes place to create a bigger population R with the union of parents and offspring. The fast non-dominated sort and the crowding-distance procedures are computed for R , followed by the selection of the best solutions for the next generation. Then, this

Additional details of the SES-VVO are as follows:

- a) **Tournament selection:** at first, two solutions are chosen randomly. Then, the one with better rank (or equal rank, but better crowding) is selected;
- b) **Repair influence effect:** it simply weights the predefined crossover (p_c^{pre}) and mutation (p_m^{pre}) probabilities by the repair influence f_{RI} , attenuating their probability to happen;
- c) **Flat crossover:** it makes the exploitation (offspring lies between its parents) to generate the part of the offspring $\vec{o}_{sub}^h = (o_1^h, \dots, o_{N_D}^h)$ from the parents $\vec{p}_{sub}^{1,h} = (p_1^{1,h}, \dots, p_{N_D}^{1,h})$ and $\vec{p}_{sub}^{2,h} = (p_1^{2,h}, \dots, p_{N_D}^{2,h})$. Each tap o_i^h is a randomly chosen value within the interval:

$$o_i^h = \text{random}[\min(p_i^{1,h}, p_i^{2,h}), \max(p_i^{1,h}, p_i^{2,h})]. \quad (4.11)$$

Two operation approaches, which rely on the SES-VVO, are developed to implement the VVO in distribution systems: one for day-ahead operation planning and other suitable for decision-making. The first strategy pursues multiple candidate solutions, whereas the second one, a user-preferred solution. Also, they work in different time horizons [Figure 9](#), so that SES-VVO may support both planning and real-time applications.

4.4.6.1 Operation planning approach for the SES-VVO (OP-SES-VVO)

As a daily operation planning tool, OP-SES-VVO consists in employing day-ahead forecasts of load and DG, based on processing historical records, to feed SES-VVO engine so that optimal control may be dispatched one day in advance ([Figure 9\(a\)](#)). In this chapter, it is assumed that the forecasts are known with sufficient accuracy. Algorithms for short-term forecasting purposes are beyond the scope of this thesis.

4.4.6.2 Decision-making approach for the SES-VVO (DM-SES-VVO)

To surpass the offline characteristic of the operation planning, which may lack robustness to maintain optimal operation in the face of forecast deviation ([VITOR; VIEIRA, 2018](#)), the proposed decision-making application performs the Volt/VAr engine for each hour h based on both the current load/DG data at hour h and their forecasts at Δ steps ahead. Thus, measured data can be used to improve performance goals. The current decision at hour h also depends on the previous decision at hour $h - 1$ to count the number of tap changes. Because of this time coupling of the tap-changing objective, the engine also takes the previous tap solution as an input (besides the current and forecast load/DG data). For each hour, one solution is chosen based on a decision objective and the corresponding taps are selected at the current hour ([Figure 9\(b\)](#)).

The decision objective is related to the operating costs (OC) given by:

$$OC = \sum_{h=h_I}^{h_F} C_{PI}^h E_{P_{in}}^h + C_{OLTC} \Lambda_{OLTC}^{h_I-h_F} + C_{SVR} \Lambda_{SVR}^{h_I-h_F} + C_{CB} Q_{inj}^{h_I-h_F} \quad (4.12)$$

where C_{PI} is the hourly energy costs (\$/kWh), $E_{P_{in}}^h$ is the energy purchased by the substation, C_{OLTC} and C_{SVR} are the costs of switching OLTC and SVRs (\$/action), C_{CB} is the cost of SCs (\$/kvar-year), $\Lambda_{OLTC}^{h_I-h_F}$ and $\Lambda_{SVR}^{h_I-h_F}$ are the number of actions performed by the OLTC and SVRs in the period from h_I to h_F , and $Q_{inj}^{h_I-h_F}$ is the amount of reactive power injected by the SCs into the grid.

Figure 9: VVO approaches: (a) Operation planning; (b) Decision-making

4.5 Results and discussion

The proposed methodology was applied to the IEEE 34 node test feeder. Initially, the validation of each specialized procedure was carried out. Several performance comparisons were conducted between typical evolutionary operators (random, Gaussian, polynomial, and non-uniform) and the proposed specialized mechanisms. Then, the complete methodology was implemented for operation planning and decision-making approaches. The reference objective vector was computed by optimizing each objective individually. This vector facilitates the visualization of the Pareto front and the comparison between solutions. Finally, robustness analysis was performed through Monte Carlo simulations.

To clarify the effectiveness of the proposed methodology, comparison was made by implementing two methods based on the MOPSO — a highly competitive EMO algorithm that has been applied to solve the VVO problem with multiple objectives (SINGH et al., 2020; JIN; CHIANG; LI, 2019). One method considers the entire day (24 hours) into the optimization process, performing a complete MOPSO (C-MOPSO). The other method

applies a strategy that a rolling VVO is executed at every 6 h (in 24 hours horizon, we have 4 time periods of 6-hour rolling window, that is, 1:00–6:00 h, 7:00–12:00 h, 13:00–18:00 h, and 19:00–24:00 h) (JIN; CHIANG; LI, 2019), carrying out a rolling MOPSO (R-MOPSO).

4.5.1 Test system

The IEEE 34 node feeder (Appendix A.1) and its data can be seen in Kersting (2001b). This distribution system has originally two SVRs (SVR.1 and SVR.2) and two fixed capacitors (at buses 844 and 848). A modified IEEE 34 node feeder was used in the simulations as follows: the SVRs were preserved, the fixed capacitors were turned into SCs (SC.1 and SC.2, respectively), one OLTC was considered at the substation, and a photovoltaic (PV) generation with 1 MVA capacity was installed at bus 830 to operate with unity power factor. The steady state voltage limits were adopted as 0.93 p.u. and 1.05 p.u. according to Brazilian regulatory standards (ANEEL, 2018).

The decision variables are the tap positions of the devices. Table 1 describes the values of the tap ratio of the transformers and the discrete amount of reactive power that the capacitor modules inject by tap. All devices have a joint movement for the three-phase tap, except the feeder regulators which have independent tap movement per phase. The NSGA-II allows encoding these decision variables through an integer representation (tap index in Table 1).

Table 1: Tap position encoding

	Equipment				
	OLTC	SVR.1	SVR.2	SC.1	SC.2
Range	0.95–1.05 [pu]	0.90–1.10 [pu]	0.90–1.10 [pu]	0–300 [kvar]	0–450 [kvar]
Step	0.025 [pu]	0.00625 [pu]	0.00625 [pu]	100 [kvar]	150 [kvar]
Tap index	0–4	0–32	0–32	0–3	0–3

The daily operation has 24 intervals of 1 h duration each. The output power curve of PV generation, shown in Figure 10, was selected from persistent clear sky condition of a typical day in Brazilian Northeast region (INPE, 2016). Figure 10 also shows the feeder daily load variations (JARDINI et al., 2000). The feeder load varies from 30% to 90% of its base value during a day. It is assumed that PV generation and load demand do not change during each 1-hour interval.

For the decision objective of the DM-SES-VVO approach, the hourly energy costs were taken from Sabillon-Antunez et al. (2017) and the costs of tap changes from Manbachi et al. (2016a). The cost of switching OLTC and SVRs is equal to 5.00 \$/tap-change and the cost of switching SCs is equal to 5.00 \$/kvar-year (according to the amount of reactive power injected by the capacitor bank into the grid). These switching costs, which

correspond to the depreciation cost for each switching operation, can be obtained based on both the cost of equipment installation and the number of switching that is allowable per day, since each tap-changing operation affects the equipment lifetime (MALAKAR; GOSWAMI, 2013). All these specified input conditions for VVO (PV generation, load demand and costs) are further detailed in the Appendix A.2.

It is worth mentioning that the IEEE 34 node test feeder was selected from the OpenDSS library, maintaining the network model exactly the same so that reproducibility of results may be achieved. This system presents a mix of constant impedance (36.46%), constant current (32.67%), and constant power (30.87%) loads. As they are predominantly voltage dependent, the CVR deployment may provide several benefits. Moreover, ZIP models can be used to represent the aggregated loads (subsection 2.1.3.2).

Figure 10: Day-ahead data: (a) Load demand; (b) PV generation

4.5.2 Results of the specialized procedures

Table 2 describes the values of all parameters used in the simulations. They were tuned by trial and error to attain promising solutions in a reasonable time. The algorithms were implemented in Python scripting language with an interface to the Open Distribution System Simulator (OpenDSS), responsible for the power flow simulations, on a computer with an Intel Core i7-6500U 2.5 GHz processor and 8 GB of RAM.

The MOPSO-based algorithms were implemented by using the mutation strategy described in Sierra and Coello (2005). The results of the R-MOPSO for a full day operation (24 h) were obtained by taking the non-dominated solutions from all combinations of solutions of each rolling window.

Table 2: Parameters of the algorithms

Algorithms		Parameters			
Search restriction*	$s_{max} = 200\,000$	$n_1 = 10$		$n_2 = 5 \times n_1$	
Repair process*	$\alpha = 0.001$	$\beta = 1.0$		$rc_{max} = 1\,000$	
Covering*	$c_{max} = 10 \times \#F_1$	$\#F1 = size(\text{Front}_1)$			
Decision-making*	$\Delta = 1, 2, \text{ and } 3$				
NSGA-II	$n_{pop} = 20$	$g_{max} = 200$	$p_c = 0.9$	$p_m = 0.33$	
MOPSO	$n_{pop} = 20$	$g_{max} = 400$	$p_m = 0.2$	$C_1, C_2 = 1.0, 0.4$	$W = 0.3$

*Parameters of the proposed methods are described in [section 4.4](#)

4.5.2.1 Search space restriction

The original combinatorial problem can reach 2.2×10^{264} possible tap configurations for one-day operation. Applying the proposed heuristic for search space restriction, this value becomes 7.1×10^{231} . This method removes, from the search space, impractical taps, i.e., taps that always result in voltage violations during the operation of the distribution system. Further complexity reduction is accomplished by the decision-making strategy, resulting in a search space size of 7.4×10^{20} , 4.0×10^{31} , and 2.4×10^{42} in average per hour of optimization for Δ ([subsubsection 4.4.6.2](#)) equals to 1, 2, and 3, respectively.

[Figure 11](#) shows the possible taps (gray area) found by the heuristic method, according to the encoding of the [Table 1](#), for each voltage regulation equipment. We can note that the possible taps for OLTC and SVRs have a behavior that tracks the daily load curve, whereas for the SCs, the tap-changing behavior is not affected by the load curve. So, the OLTC and SVRs influence the feasibility of the solution more than the capacitors, leaving for these ones the local voltage regulation.

4.5.2.2 Repair process

The Volt/VAr constraint handling is a challenging task for traditional variation operators used in the NSGA-II, when considering the one-day total voltage violations throughout the evolution process. [Table 3](#) shows, by the average value of the best solutions after 20 runs, that the total voltage violations (f_{VV}^T) persist at the end of the generations, producing infeasible solutions. The mutation operators considered are: random, Gaussian, polynomial, and non-uniform (see [Lim et al. \(2017\)](#) for more details)¹. The pattern design of the constraint handling approach presented by the original algorithm ([DEB et al., 2002](#)) is not able to reach fully constraint satisfaction. The MOPSO-based methods achieved greater reductions in voltage violations, specially the R-MOPSO, than the traditional operators in the NSGA-II, but not enough to obtain feasible solutions in all runs.

¹ *Random* uses a uniform distribution, while *Gaussian* uses a normal distribution.

Figure 11: Restricted search space for each equipment (gray area)

On the other hand, [Table 3](#) also shows the behavior of the voltage violations when the repair process is applied to the algorithm. The proposed SES-VVO approach does not only satisfy completely the constraints but, furthermore, accomplishes that at the early generations, up to 10th generation. This is very desirable, because, once the constraints are met, the remaining task for the algorithm is finding optimal solutions. Also, the proposal is robust for not requiring feasible solutions in the initial population. From now on we will consider the repair process in the algorithms.

4.5.2.3 Performance improvement of the f_{SO} minimization

Reducing the one-day total tap-changing operations (f_{SO}) is another challenge when we consider it as one of the objective functions. [Table 3](#) describes the mean value of the best solutions regarding the number of operations after 20 runs. It shows that typical mutation operators (random, Gaussian, polynomial, and non-uniform) are not able to efficiently avoid the excessive tap changes of the Volt/VAr equipment. These typical mutation operators do not allow individuals trapped into a local optimum to escape from it. Likewise, the MOPSO-based methods are not capable to efficiently minimize the switching operations. Then, choosing solutions like these may reduce the lifetime of the devices, increase costs (related to maintenance and/or depreciation) and damage power supply (in quality and/or reliability).

[Table 3](#) also shows the behavior of the evolution when the HTP mutation is present in the algorithm. This proposed operator yields substantial tap operations reduction, exhibiting up to almost 4 times less actions of the equipment during one-day operation, when compared with the typical mutation solutions. Therefore, it significantly improves the efficiency of the algorithm in searching for promising solutions featured by reduced

tap-changing operations and minimal active power intake into the system.

4.5.2.4 Performance improvement of the f_{PI} minimization

Table 3 also shows the mean value of the best solutions regarding the active power intake values (f_{PI}) after 20 runs. Among the typical mutation operators considered, the non-uniform presents the best capability of minimizing the active power intake. When considering the MOPSO-based methods, the performance of the R-MOPSO is better than typical mutation operators of the NSGA-II. However, the proposed mechanism of adding a TAI causes even more pressure in search of better solutions, obtaining 151 kWh less than the non-uniform operator and 84 kWh less than the R-MOPSO. Therefore, this mechanism corroborates with the increase of energy efficiency.

Table 3: Results of the performance indices after 20 runs

Strategy	f_{VV}^T (Eq. 4.5)		f_{SO} (Eq. 4.1a)		f_{PI} [MWh] (Eq. 4.1b)	
	Average	Std	Average	Std	Average	Std
Random	130.20*	13.88*	140.00	2.81	23.209	0.017
Gaussian	95.25*	8.22*	129.45	4.31	23.249	0.033
Polynomial	73.55*	7.40*	127.00	5.34	23.175	0.030
Non-uniform	34.55*	5.76*	118.30	5.85	23.039	0.020
SES-VVO	0.00	0.00	36.45	3.94	22.888	0.021
C-MOPSO	15.90*	3.73*	135.40	4.71	23.182	0.027
R-MOPSO	1.85*	1.59*	114.00	4.22	22.972	0.013

*Without repair process

4.5.2.5 Covering Pareto front

This specialized procedure was used to combine heuristically the nondominated solutions found after 20 runs. It improves the previous solutions, as a local search, without additional computational cost relative to power flow simulation, since the necessary information is bound to the sub-vectors. Table 4 compares the hypervolume quality (Equation 4.10) of the original approximation set $\mathcal{Q}(\mathcal{H}_O)$ (before the covering procedure) and the improved one $\mathcal{Q}(\mathcal{H}_I)$ (after the covering procedure). For all sets, the procedure can improve the respective hypervolume quality, which means better solutions available for the distribution system operator to choose, resulting in a covered Pareto gain — percentage gain of $\mathcal{Q}(\mathcal{H}_I)$ in relation to $\mathcal{Q}(\mathcal{H}_O)$. The hypervolume quality of the SES-VVO is much greater than the other strategies (typical genetic operators of NSGA-II and MOPSO-based methods), confirming the capability of the SES-VVO to solve the VVMO problem. Table 4 also shows the average time required for the covering procedure in each run. The more

solutions in the set, the more time is required to perform the procedure. That is why SES-VVO needs more time than the others.

Table 4: Hypervolume of the approximation sets and times required for Pareto covering procedure

Strategy	Hypervolume quality (Eq. 4.10)			Time [s]	
	$\mathcal{Q}(\mathcal{H}_O)$	$\mathcal{Q}(\mathcal{H}_I)$	Gain(%)	Average	Std
Random	9.70	19.86	104.79	11.80	8.09
Gaussian	12.57	21.96	74.69	11.45	5.26
Polynomial	17.91	25.03	39.73	11.92	5.04
Non-uniform	30.36	30.48	0.41	5.21	3.53
SES-VVO	78.91	82.24	4.21	188.02	86.20
C-MOPSO	14.78	*	*	*	*
R-MOPSO	36.92	*	*	*	*

*Not applicable

4.5.3 Results of the OP-SES-VVO and the DM-SES-VVO

Figure 12 shows the nondominated optimal solutions found by the different strategies. They represent compromises between active power intake on the system (f_{PI}) and switching operation (f_{SO}) objectives for 24 hours of operation. In order to better visualize the results, reference solutions are depicted through lines in the graph, according to the following methods: a) Optimal f_{PI} — the active power intake is the objective function minimized in a single-objective optimization problem, b) Optimal f_{SO} — the total tap-changing operations is the objective function minimized in a single-objective optimization problem, and c) Conventional voltage regulation (Conv-VR) — it automatically changes the tap settings to correct voltage violation (no optimization in this case) (KERSTING, 2001a), representing a typical number of tap changes. Appendix B details the parameters of Conv-VR. The reference objective vector is defined by $\vec{z}_{ref}^* = (f_{PI}^{min}, f_{SO}^{min})$, where f_{PI}^{min} and f_{SO}^{min} are the results of the Optimal f_{PI} and the Optimal f_{SO} , respectively.

The proposed OP-SES-VVO approach can find multiple diversified non-dominated solutions near to the optimal objectives taken from the reference solutions, that is, near-minimal active power intake is reached with reduced amount of tap changing operations. The approximated Pareto front found by the OP-SES-VVO is much better than those from typical evolutionary operators (random, Gaussian, polynomial, and non-uniform) and those from MOPSO-based methods in terms of Pareto front approximation and diversity. Moreover, some solutions reached lower numbers of switching operation than that of Conv-VR with significant reduction of active power intake. The distribution system operator can choose any of the solutions, making a decision for the next 24 hours according

to its policies.

On the other hand, the DM-SES-VVO approach incorporates the distributed system operator decision policy internally, giving only one solution per hour. The DM-SES-VVO performance is plotted in Figure 12, after an average of 20 runs, for 24 hours of operation. Three DM-SES-VVO solutions are displayed for Δ equals to 1, 2, and 3 steps ahead of load/DG data forecasts (Δ_1 , Δ_2 , and Δ_3). Because DM-SES-VVO works in a reduced complexity of time coupling (i.e., the optimization horizon is shorter than the operation planning, consequently the search space is smaller too), it is capable to find enhanced non-dominated solutions when compared to the Pareto front approximation.

The proposed mechanisms of the SES-VVO can also be employed in the single-objective optimization problem for composing the SOP-SES-VVO approach. By taking the OC (Equation 4.12) as the objective function, the SOP-SES-VVO solution, after an average of 20 runs, is obtained and drawn in Figure 12. As a result, the solution is close to the approximated Pareto front.

Figure 12: Operation planning and decision-making solutions

Table 5 compares the OC (Equation 4.12) of all approaches, taking the Conv-VR solution as reference costs. Although the active power intake costs (C_{PI}) are much higher than the tap-changing operation costs (C_{SO}), this last one has a decisive impact on the total operating costs, given by $OC = C_{PI} + C_{SO}$. This happens because C_{SO} varies much

more than C_{PI} in the different solutions. Therefore, C_{SO} is a crucial objective to be considered in the VVO problem, which is confirmed by the reduced OC of the Optimal f_{SO} . DM-SES-VVO approach achieves the best total cost minimization, up to 10.98% less than the Conv-VR for one day system operation. It can greatly reduce OC by decreasing C_{SO} . OP-SES-VVO approach gives alternative solutions with further reduced f_{PI} , which can be less susceptible to energy costs variation. OP-SES-VVO costs ranges from -9.70% to 7.39% when compared to Conv-VR. SOP-SES-VVO approach also gives a promising result, 9.50% of savings. In summary, the SES-VVO is an effective method to reduce operating costs. It is important to mention that, if tap-changing actions are not properly considered in the VVO, the operating costs can reach huge values, resulting in an inefficient VVO operation, as demonstrated by the Optimal f_{PI} costs.

The OCs of the MOPSO-based methods, C-MOPSO and R-MOPSO, are 11.49% and 5.54% greater than the Conv-VR, respectively. They are not capable to produce cost saving solutions. This is because, although they can reduce C_{PI} , they are not efficient in reducing the number of tap changing operations, which is the feature that has a decisive impact on the operating costs.

Table 5: Operating costs of all approaches taking the Conv-VR solution as reference costs

Approach	f_{SO}	f_{PI} [MWh]	C_{SO} [\$]	%	C_{PI} [\$]	%	OC [\$]	%
Conv-VR	64	23.691	260.00	0.00	1597.48	0.00	1857.48	0.00
Optimal f_{SO}	19	23.533	71.99	-72.31	1596.40	-0.07	1668.39	-10.18
Optimal f_{PI}	167	22.827	640.14	146.21	1550.45	-2.94	2190.59	17.93
SOP-SES-VVO	29	23.386	95.09	-63.43	1585.93	-0.72	1681.02	-9.50
OP-SES-VVO (OC_{min})*	27	23.460	90.75	-65.10	1586.54	-0.68	1677.30	-9.70
OP-SES-VVO (OC_{max})*	117	22.864	442.19	70.07	1552.48	-2.82	1994.67	7.39
DM-SES-VVO ($\Delta = 1$)	21	23.269	76.11	-70.73	1577.50	-1.25	1653.61	-10.98
DM-SES-VVO ($\Delta = 2$)	22	23.241	83.77	-67.78	1575.49	-1.38	1659.26	-10.67
DM-SES-VVO ($\Delta = 3$)	24	23.208	90.35	-65.25	1574.12	-1.46	1664.47	-10.39
C-MOPSO (OC_{min})*	127	23.206	495.92	90.74	1575.17	-1.40	2070.99	11.49
R-MOPSO (OC_{min})*	102	23.072	391.92	50.74	1568.52	-1.82	1960.44	5.54

* OC_{min} (OC_{max}) refers to the solution among the multiple ones with minimum (or maximum) OC.

For 20 runs, the average time spent by the OP-SES-VVO algorithm was 599.38 s, whereas the DM-SES-VVO algorithm took 32.26 s, 45.95 s, and 72.90 s, for Δ equals to 1, 2, and 3, respectively. Therefore, the methodology has potential for real-time applications, assuming 15 min as a near real-time solution — as smart meters typically send data every 15 min, Volt/VAr optimization solutions have to operate within this time (MANBACHI et al., 2016a).

4.5.4 Analyzing the robustness for scenario realizations of the uncertainties

Finally, an uncertainty study is conducted to consider the stochastic nature of PV generation and the variability of the load demand in the VVMO. These uncertainties are modeled using a scenario-based stochastic approach. First, Monte Carlo sampling is applied to generate 100 random scenarios of hourly PV output and load demand based on a Gaussian distribution function (with the standard deviations equal to 5% and 2%, respectively, of the expected values). [Figure 10\(a\)](#) illustrates the minimum and maximum uncertainty interval of load demand and [Figure 10\(b\)](#) shows the range of PV output power variations. Then, a method for scenario reduction, known as simultaneous backward reduction ([HEITSCH; RÖMISCH, 2003](#)), is carried out to reduce the computation efforts while maintaining the solution accuracy ([WANG et al., 2014](#)). The 100 generated scenarios are reduced to 20 scenarios that are best approximations of the system uncertainty.

The features for the uncertainty study are:

- a) the rate of feasible daily scenarios (FDS_{rate}), which is the percentage of daily scenarios that the method can operate without any voltage violation;
- b) the rate of feasible voltage nodes (FVN_{rate}), which is the percentage of nodes with voltage within the acceptable limits in all scenarios;
- c) the rate of feasible hours (FH_{rate}), which is the percentage of hours in which the voltages are within the acceptable limits in all scenarios; and
- d) the objectives (f_{SO} , f_{PI} , and OC).

A sensitivity analysis is performed to explore the influence of load demand and PV generation uncertainties in the post-optimization of the SOP-SES-VVO and OP-SES-VVO solutions. Thus, these solutions are submitted to load/PV variations in the scenarios. The results in [Table 6](#) show that these solutions are not able to keep feasibility when facing the daily scenarios (there is no single scenario in which voltages are within the acceptable limits during the entire day, $FDS_{rate} = 0\%$). Although SOP-SES-VVO presents better results than OP-SES-VVO in terms of more nodes (FVN_{rate}) and more hours (FH_{rate}) with voltages within the acceptable limits, they have the same feasibility problem, that is, part of the nodes does not meet the standard voltage limits all the time (i.e., both FVN_{rate} and FH_{rate} features are not equal to 100%). These results highlight the weakness of the post-optimization operation planning in the face of load/DG uncertainties when CVR goals are being strictly pursued.

The Conv-VR method has also been tested to load/PV variations. It presents better feasibility results than the operation planning (i.e., more daily scenarios, more nodes, and more hours with voltages within the acceptable limits), since it automatically changes the tap settings trying to correct voltage violation. Nevertheless, [Table 6](#) points out that the feasibility of its operation is fulfilled in only 25% of the daily scenarios.

Finally, the DM-SES-VVO approach has been hourly applied for each uncertainty realization regarded as real-time operation. As a result, this method can keep the operation feasible in all scenarios (all indices of feasibility are equal 100% in Table 6).

Table 6: Results of the feasibility features

Methods	FDS_{rate} [%]	FVN_{rate} [%]	FH_{rate} [%]
SOP-SES-VVO	0.00	82.21	76.87
OP-SES-VVO (OC_{min})*	0.00	76.10	69.79
OP-SES-VVO (OC_{max})*	0.00	67.33	52.08
Conv-VR	25.00	94.71	93.75
DM-SES-VVO ($\Delta = 1$)	100.00	100.00	100.00

* OC_{min} (OC_{max}) refers to the solution among the multiple ones with minimum (or maximum) OC .

The scenario aggregation (SA) technique is implemented to find the expected result of the problem considering uncertainty (NIKNAM; ZARE; AGHAEI, 2012; MOHAMMADI; SOLEYMANI; MOZAFARI, 2014). First, the problem is solved for each scenario in a deterministic and independent way through the mechanisms of the SES-VVO. Then, the optimal solutions obtained from these scenarios are aggregated according to their normalized probability to compose the final solution of the problem. This optimal aggregated solution is used as a reference solution for performance in Table 7.

Now, the robustness of the DM-SES-VVO approach is checked based on performance. Table 7 shows the range of variation of the optimization objectives f_{PI} , f_{SO} , and CO . The results are kept close to the optimal expected ones, that is, the DM-SES-VVO solution presents small deviations from the SA solution. Therefore, the advanced strategy for decision making proposed in subsection 4.4.6.2 presents robustness to maintain a reliable operation of the system in the face of load/DG uncertainties and yet seeking for optimal performances.

Table 7: Results of the performance features

Objectives	SA	DM-SES-VVO ($\Delta = 1$)	
		Min	Max
f_{SO}	22	15 (-31.82%)	29 (+31.82%)
f_{PI} [MWh]	23.716	23.289 (-1.80%)	24.193 (+2.01%)
OC [\$]	1693.82	1644.39 (-2.92%)	1747.30 (+3.16%)

4.6 Conclusions

This research has proposed a new optimization algorithm (SES-VVO) based on the NSGA-II to efficiently solve the VVMO problem when the number of tap-changing operations is considered together with the CVR goals. This problem is a challenging task for EAs in terms of meeting voltage limit constraints and reaching near optimal solutions due to the time coupling combinatorial complexity. Restricting the search space was the first step of the methodology. Then, the simulations demonstrated that the daily voltage violations persist at the end of the generations for benchmark approaches, used in this chapter for comparison purposes: typical genetic operators of NSGA-II and MOPSO-based methods. This problem was properly solved by the proposed repair process, which enabled these benchmark methods to generate feasible solutions. Furthermore, the typical genetic operators of NSGA-II and MOPSO-based methods did not allow individuals trapped into a local optimum to escape from it, producing excessive switching of the Volt/VAr equipment and sub-optimal active power intake values. To improve these performance objectives, the specialized mechanisms of search, HTP and TAI, was proposed in the SES-VVO. The HTP operator yielded substantial tap operations reduction (at least 3 times less) and the TAI operator pressured even more the search for near-optimal active power intake values (at least 84 kWh of energy savings) when comparing with the other methods (typical genetic operators of NSGA-II and MOPSO-based methods). The last step of the proposed method is a procedure to better cover the Pareto front. The OP-SES-VVO produced a larger amount of multiple diversified high quality solutions for daily operation planning and it achieved much greater hypervolume quality than the typical operators of NSGA-II and MOPSO-based methods. In general, among these benchmark methods, the R-MOPSO was the one with better results. But even so, the superiority of the proposed SES-VVO was verified in all performance indices.

The potentialities of the proposed SES-VVO could also be explored through an hourly decision-making strategy that incorporated costs as a decision objective in an optimization horizon constituted by the threefold input: previous control, actual data, and forecasts. As a result, an advanced speed-up approach, DM-SES-VVO, was developed capable to achieve superior performance in a real-time scale.

The cost study results revealed that the operating costs can be reduced by VVMO designs. In particular, the cost savings achieved almost 11% in comparison with the conventional voltage regulation when DM-SES-VVO was employed. In contrast, the MOPSO-based methods were not able to produce cost savings. Moreover, it was demonstrated that the switching costs have a decisive impact on the economics when the CVR goals are pursued by the VVO. If tap-changing actions are not carefully considered, the operating costs can reach huge amounts.

Finally, an uncertainty study was conducted through a scenario-based stochastic

approach that modeled the load/DG stochasticity. Post-optimization sensitive analysis of the operation planning led to infeasible solutions. When the CVR goals are being rigorously pursued by VVO, scenarios different from that used in the optimization may deteriorate the coordinated control, resulting in voltage issues. Notwithstanding, SES-VVO can be applied to solve the series of equivalent deterministic scenarios that compose the stochastic optimization framework. Moreover, the DM-SES-VVO approach presented robustness to deal with scenario changes, keeping near optimal results and satisfying constraints. This advanced speed-up strategy can take advantage of the smart grid technologies to implement efficient and robust solutions in a real-time operation.

5 IMPROVING ROBUSTNESS OF THE VVO-BASED CVR

This chapter brings to light an important issue that is often forgotten by the extensively studied VVO-based CVR problem. In fact, it is carefully observed in this chapter that when the attention of the VVO design is given only for performing CVR, an unexpected problem arises, the lack of robustness for scenario changes. In other words, small deviations in loading and/or DG power production, from the forecasts, can lead to violation of voltage standards. So, as the integration of renewable-based DGs is evermore increasing in the distribution system, their stochastic behavior can lead to poor voltage quality during the system operation due to the non-robust VVO designs.

In this context, robustness parameters and metrics are proposed in order to analyze the effects of uncertainties of load/DG on voltage regulation. The idea is to quantitatively evaluate the robustness of VVO design solutions. The major advantage of these parameters/metrics is that they do not require a presumed probability distribution or any other information of the uncontrollable parameters beyond the forecasts; nor they need evaluating large numbers of scenarios to approximate the performance of the solution against a variety of uncertainty realizations.

The higher point of this chapter is to evaluate the possibility of incorporating such parameters/metrics into the VVO-based CVR so that the CVR goals may be pursued without neglecting the robustness of the system operation. This enhancement of the VVO-based CVR is explored taking into account the potential of designing Volt/VAr control as multi-objective optimization problems, which can lead to huge advantages for the distribution system operation.

5.1 Motivations

Very often, the optimization problem is solved in a conservative way, according to the typical load and DG power production pattern, without considering deviations from this pattern during the system operation. However, any difference from the forecast may deteriorate the coordinated control, in some sense, turning it into infeasible solution.

Important researches have solved the CVR problem based on VVO ([PADILHAFELTRIN](#); [RODEZNO](#); [MANTOVANI, 2015](#); [MANBACHI et al., 2016b](#)), but without taking into account the stochastic nature of the uncertainties. Nevertheless, the distribution system operator needs VVO techniques that are efficient, in terms of performance, but also robust to work under uncertainty environment.

[Zheng et al. \(2017\)](#) associated three major factors that contribute to the uncertainties in active distribution networks: 1) the active outputs of renewable DGs fluctuate

dramatically due to their inherent volatility and intermittency; 2) load demands vary with time and are hard to predict precisely; and 3) because real-time measurements in distribution networks are limited, large errors may occur in the estimations of the outputs of the DGs and load demands. Thus, without a robust control to face uncertainties, voltage regulation in a distribution system can be adversely affected (DARATHA; DAS; SHARMA, 2015), decreasing the power quality due to voltage violations (CHANHOME; PHICHAISAWAT; CHAITUSANEY, 2013).

Designing approaches that guarantee feasibility and optimality of the network operation, even under uncertainties, is of great interest (SARIC; STANKOVIC, 2009; BAKER et al., 2018). To perform well in the real-world problems, the uncertain characteristics must be taken into account. However, this imposes major challenges for the VVO design. The intermittent and uncertain power generation of RES along with the load uncertainty further increases the complexity of the Volt/VAr control (MEENA et al., 2016; NIKNAM; ZARE; AGHAEI, 2012).

In general, optimization under uncertainty is typically solved using either stochastic or robust approaches (LI et al., 2020). In stochastic optimization, the information about probability distributions of the uncertain parameters are assumed to be known (or presumed) and, based on a certain sampling method, the fitness of the solution is determined by some statistical measure (e.g., expected value) (HUGHES; GOERIGK; DOKKA, 2020). In robust optimization, the uncertainty of these parameters can be described by a finite set of different scenarios, requiring less information about probability distributions. Then, the robust optimization searches for the optimal solutions considering the worst scenario as a deterministic problem (DARYANI; OMRAN; MAKUI, 2020). Both approaches have been used to solve the VVO problem under uncertainty of load/DG.

The proposal in Xu et al. (2017) coordinates multiple VVC devices at different timescales aiming to minimize the total expected power loss. In the hourly timescale (first stage), capacitor banks (CBs) and OLTCs are scheduled before stochastic RES output and load variations are realized. In the 15-min timescale (second stage), RES inverters provide var support to supplement the first-stage decision after the uncertainty is realized. The proposed VVC is modeled as a two-stage stochastic programming problem. By calculating the expectation term of the second-stage problem based on a representative number of scenarios, the problem is converted to a deterministic problem that can be solved by commercial solvers. Similarly, Zhang and Xu (2020) converts the stochastic programming model to a deterministic equivalent by using a finite number of possible scenarios. But in this case, a central hierarchy dispatches the inverter reactive power output to minimize network power loss and a local hierarchy responds to real-time voltage deviation through a linear droop controller. These two control hierarchies are optimally coordinated under stochastic PV power generation and load variations. In the above-mentioned works, the

scenario-based stochastic optimization provides the optimal expectation considering the uncertainty probability distribution and its realization. Other works have additionally applied the scenario aggregation method to define the solution of the problem (NIKNAM; ZARE; AGHAEI, 2012; SOLTANI; RASHIDINEJAD; ABDOLLAHI, 2018). In general, modeling the uncertainties related to load/RES in the scenario-based stochastic framework relies on pre-defined probability distribution (QUIJANO; PADILHA-FELTRIN, 2019). If the current random scenarios do not follow such distribution, the robustness of the obtained solution may be impaired (XU et al., 2017). Moreover, the solution is usually computationally heavy (LI et al., 2020).

Gao, Liu and Wang (2018) proposed a two-stage robust optimization to coordinate active and reactive power under uncertainties of wind power output and load demand. The aim is to improve the energy efficiency in the active distribution system. The first stage decision, made prior to the realization of uncertainties, considers the worst-case scenario to adjust OLTC ratios, discrete reactive power compensators, and charge–discharge power of energy storage system. Then, the continuous reactive power compensators are intended for the second stage decisions that can flexibly be adjusted in the real-time operation when the uncertainties are revealed. This two-stage robust optimization model is similar to Ding et al. (2016), where the first stage determines the “here-and-now” decisions (discrete reactive power compensators), which cannot be adjusted after the uncertainty is revealed, while the second stage represents the “wait-and-see” decisions (continuous reactive power compensators) that can be determined after the wind power uncertainty is revealed. Zhang et al. (2019) proposed to coordinate three control stages to reduce energy loss and mitigate voltage deviation under high-level PV penetration. The first stage schedules hourly the slow-acting devices (CBs and OLTC) aiming to reduce energy loss. The second stage dispatches the fast-acting devices (PV inverters) to reduce energy loss in a shorter period (15 min), compensating the first stage decisions in case of significantly uncertain PV generation and load demand variations. In the third stage, the droop control of PV inverters locally responds to sudden voltage deviation in real time. The first two stages are coordinated through a robust optimization model which optimizes the operation decision based on the worst case of PV output and demand variation. Likewise, recent studies have also been using robust optimization models. They consider the worst case to guarantee solution robustness against uncertainty realization (LI et al., 2020; ZHANG; DONG; XU, 2019). However, robust optimization tends to be overly conservative and may not be cost-effective (AN; ZENG, 2015). As the size of the uncertainty set, which is non-trivial to be determined, defines the solution quality, choosing it inappropriately may, on the one hand, lack of the ability to handle with uncertainty or, on the other, produce an overly conservative solution (AN; LO, 2016).

Besides the stochastic and robust approaches, smart inverters have been suggested as a supplementary device to address the voltage deviations issues. Due to their high response

speed and flexible reactive power injection range (ZHANG et al., 2019), smart inverters have been used to provide a fast control in multi-stage coordination frameworks which can coordinate different VVC devices in multiple time-scales (slow and fast) (ZHANG; DONG; XU, 2019; JIN; CHIANG; LI, 2019). Moreover, the smart inverter can be integrated into the multi-stage designed by either the stochastic approach (SINGH et al., 2020) or the robust approach (ZHANG et al., 2019). However, smart inverters with reactive power compensation capability may not be available in the system or such control may be limited by standards. In addition, it is desirable to design solutions that, even using traditional devices (e.g., SCs, OLTC, and SVRs), are able to deal with the fast and uncertain voltage regulations issues caused by DG penetration in the distribution systems.

Another class of methods for solving the VVO is the evolutionary algorithms. To take into account the uncertainty in those methods, Monte Carlo simulation is the most straightforward and accurate technique (MALEKPOUR; NIKNAM, 2011). For this, the load demand and RES generation uncertainties can be modeled through Monte Carlo sampling as a scenario-based stochastic framework. Then, EAs can be applied to solve the series of equivalent deterministic scenarios (NIKNAM; ZARE; AGHAEI, 2012; ZHOU et al., 2017). There are other examples and strategies using EAs to solve the probabilistic load flow by modeling the uncertainties via analytical methods (HONG; LUO, 2009) and approximate techniques (MALEKPOUR; NIKNAM, 2011; MALEKPOUR; TABATABAEI; NIKNAM, 2012; ZARE et al., 2014). However, all these approaches have some difficulties and shortcomings similar to those mentioned above for stochastic and robust approaches.

So, when analyzing the literature survey presented above, the integration of robust metrics into VVO-based CVR has not been designed as a MOP to be solved by EMO algorithms. There is a research gap on robust metrics which do not require much information about modeling of the uncertainties. For this reason, in this chapter, efforts are carried out to develop a novel robustness framework — constituted by parameters and metrics — that reflects the measure of robustness of the VVO design against the stochastic nature of electrical demand and renewable generation. Then, the robustness measure is added into the evolutionary multi-objective problem as an additional criterion to be optimized together with the performance (DEB et al., 2009). The result is an evolutionary approach that deals with the trade-off between solution quality and robustness.

Lim et al. (2006) and Li, Azarm and Aute (2005) are examples of EA methods that search for good performance and maximum robustness. In a general way, they modeled the robustness as the maximum acceptable performance variation. In Lim et al. (2006), the robustness was investigated by the relation between uncertainty and performance degradation. In Li, Azarm and Aute (2005), the robustness index used a non-gradient based parameter sensitivity estimation to quantitatively measure the robustness of design solutions. In fact, designing the trade-off between performance and robustness to be solved

by EAs is a strategy that exists in literature (SAHA; RAY; SMITH, 2011; BRANKE; LU, 2015). But, there is a lack of such works in the context of VVO-based CVR.

After establishing the proposed robustness framework for Volt/VAr control, this chapter formulates the conventional CVR problem as a base for robustness analysis and comparison purposes. Then, an improved approach is developed by adding the robustness criteria into the optimization. The first problem is the single-objective VVO-based for snapshot¹ CVR and the second one is the multi-objective VVO-based for robust snapshot CVR. To facilitate referencing of these methods, they will be called Steady-CVR and Robust-CVR, respectively.

As the focus is the robustness analysis, a simpler formulation of the VVO/CVR problem will be considered, that is, the number of switching actions of the Volt/VAr devices will be neglected. Therefore, the problem will be solved at a point in time, also known as the snapshot mode of the power flow, because there will be no time coupling of the control (neither in the constraints nor in the objectives). The complete problem will be considered in the next chapter.

The Steady-CVR method is solved by the genetic algorithm (GA). The results show the lack of robustness for conventional CVR models. The conclusion is that merely pursuing CVR goals may lead to unexpected poor robustness of the system operation when unforeseen scenario changes happen. So, in order to ensure power quality, even for some sort of scenario changes, and to simultaneously implement the CVR, the Robust-CVR proposal formulates a multi-objective optimization problem that deals with both objectives, minimize the load demand and energy losses through the CVR and maximize robustness. The outcome set of trade-off solutions are found using the NSGA-II algorithm. This set represents the control settings of the Volt/VAr devices that yield a system operation with near-minimum load demand and energy losses, and robust to scenario changes. The robustness framework also gives subsidies for decision-making support.

5.2 Robustness framework definition

In general, a Volt/VAr optimization problem requires daily load/DG estimation for the computation of the optimal coordination among the equipment. Consequently, the optimal results are guaranteed during the operation only if the current load/DG corresponds to the same estimated value used in the former computation. Therefore, deviations from the estimate must be investigated for the computed set-points of the control to measure its robustness for uncertainties. For this purpose, robustness parameters and metrics are proposed in this section.

¹ In the snapshot mode of the OpenDSS, the power flow is calculated for a specific condition in time (RADATZ et al., 2016).

Due to the increasing penetration of DERs, the voltage constraint satisfaction has been seen as one of the major future challenges of power system operators (PEDERSEN; SLOTH; WISNIEWSKI, 2016). Based on this premise, the present robustness framework focus on designing VVO solutions which guarantee that the voltage constraints are still within the feasible range under the influence of load/DG uncertainty. This concept is known as feasibility robust optimization (GUNAWAN; AZARM, 2005), giving attention to the robust feasibility of constraints (LI et al., 2020). In fact, one of the ways to measure robustness in optimization problems involving uncertainty is by considering the maximum range in parameter variation that still leads to an acceptable solution (DEB et al., 2009).

5.2.1 Robustness voltage vector

First, the robustness voltage vector ($\vec{R}_v$) is proposed to make use of a representation scheme for the load deviations supported by the control setting. Given a vector $\vec{T}^h$, whose elements are the optimal settings of the Volt/VAr devices at hour h , it is possible to verify the minimum and maximum limits of the loading that such controls support the operation without voltage violation. These limits are called lower robust limit (RL_l^h) and upper robust limit (RL_u^h), respectively. Figure 13 illustrates these values for the reference loading k_{ref}^h , which is the forecast value used in the optimization.

Figure 13: Illustration of the limits supported by the control facing load deviation from the forecast

The extension from the reference loading to the lower robust limit defines the lower robust margin (RM_l^h) given by

$$RM_l^h = k_{ref}^h - RL_l^h \quad (5.1)$$

and that from the upper robust limit to the reference loading defines the upper robust margin (RM_u^h)

$$RM_u^h = RL_u^h - k_{ref}^h. \quad (5.2)$$

These lower and upper robust margins establish the robust range for loading deviations from the forecast. That is, the control setting is capable of facing scenario realizations within these margins, keeping the voltage within the permitted limits.

Now, it is proposed to represent the robust range through a Euclidean vector in the x - y plane. The lower and upper robust margins are the components of the robustness voltage vector $\vec{R}^h$ on the coordinate axes x and y , respectively, defined by the following vector notation:

$$\vec{R}^h = RM_l^h \hat{x} + RM_u^h \hat{y} \quad (5.3)$$

where $\hat{x} = (1, 0)$ and $\hat{y} = (0, 1)$ are unit vectors that represent the standard basis in $\Re^2$.

Figure 14 shows the definition of components of the vector $\vec{R}^h$. As the rectangular components assume only positive values, $\vec{R}^h$ always remain in the first quadrant of the x - y plane. The magnitude and angle of the vector $\vec{R}^h$ in the polar coordinate system are given by:

$$|\vec{R}^h| = \sqrt{(RM_l^h)^2 + (RM_u^h)^2}, \quad (5.4)$$

$$\angle \vec{R}^h = \arctan\left(\frac{RM_u^h}{RM_l^h}\right). \quad (5.5)$$

Figure 14: Robustness voltage vector components

The robustness voltage vector $\vec{R}^h$ is a practical way to represent the robust margins in the same element, providing a magnitude measure and a relation between upward and downward load deviations.

5.2.2 Robustness index definition

The robust margins define how successfully the control faces scenario changes. If the control is capable of ensuring a proper system operation only for downward load deviations, then the robustness is weak, regardless of how large the margin is. Since stochastic load

behavior may increase or decrease values from the expected value, it is important to keep balance between upward and downward load deviations. Based on this criterion, the robustness index is proposed as follows.

Given a robustness voltage vector $\vec{R}^h$, the robustness index R_I is defined as

$$R_I^h = \frac{|\vec{R}^h|}{k_{ref}^h} \sin(2\angle\vec{R}^h) \quad (5.6)$$

where $|\vec{R}^h|$ and $\angle\vec{R}^h$ are the magnitude and angle of the vector $\vec{R}^h$, and k_{ref}^h is the reference loading (i.e., the expected load) at hour h .

The following explanation is made by considering $k_{ref}^h = 1$. The polar components of the vector $\vec{R}^h$ are used to build a sine in Equation 5.6, where the amplitude is $|\vec{R}^h|$ and the function argument is the double of $\angle\vec{R}^h$. Thus, the first quadrant of the rectangular coordinate is translated to the half-sine that ranges from 0 to $\pi/2$. This half-sine computes R_I^h by attenuating the magnitude $|\vec{R}^h|$ according to the angle distance from $\pi/4$. When $\angle\vec{R}^h$ is around $\pi/4$, there is a good balance between lower and upper robust margins, so the value of R_I^h is close to $|\vec{R}^h|$. But, as the angle $\angle\vec{R}^h$ moves away from $\pi/4$, the value of R_I^h becomes increasingly smaller than $|\vec{R}^h|$. Figure 15 illustrates the calculation of R_I^h when the angle $\angle\vec{R}^h$ is within $[\pi/4, \pi/2]$.

Figure 15: Robustness index illustration

The robustness index is, therefore, a metric that allows evaluating the results of the Volt/VAr control and that permits the comparison among solutions for optimization purposes.

5.2.3 Reliable robust margin

It is possible to take the smallest robust margin as the tolerable load deviation, regardless of direction, that ensures the voltage within the permitted limits. In other

words, if the current loading breaches this margin, it may cause voltage violations. So, the magnitude of reliable robust margin RM_R^h is expressed as follows:

$$RM_R^h = \min(RM_l^h, RM_u^h). \quad (5.7)$$

The magnitude of reliable robust margin RM_R^h can be used as a complementary robustness indicator of the system operation, useful for decision-making. For ease of interpretation, we can rewrite this indicator as a percentage change. Thus, the percentage of reliable robust margin $RM_{R\%}^h$ is given by the percentage of the reliable robust margin in relation to the reference loading:

$$RM_{R\%}^h = \frac{RM_R^h}{k_{ref}^h} \times 100 \text{ [\%]}. \quad (5.8)$$

Therefore, the reliable robust margin is the allowable percentage of load deviation from the forecast that still keeps the feasibility of the Volt/VAr control in relation to voltage standards.

5.2.4 Sensitivity index for optimization

All the beforehand parameters/metrics related to robustness are functions of $\vec{T}^h$, which is the optimal settings of the Volt/VAr devices at hour h . Different control settings $\vec{T}^h$ will have different robust parameters/metrics. This means that a certain control setting can produce a good performance of the system operation, but at the same time it can be non-robust, i.e., the feasibility of the operation can be easily lost in the face of uncertainties. The opposite can also happen. So, in the VVO designs, the trade-off between performance and robustness must be investigated.

For this purpose, it is possible to pursue this balance by incorporating the robustness index into the VVO problem. In minimization optimization, the inverse of the robustness index can be used as a measure of the sensitivity of the Volt/VAr control solutions for scenario changes. The greater the sensitivity, the greater the chance of the solution becoming infeasible during uncertainty realizations. So, the sensitivity index is given by:

$$f_{Sens}^h = \frac{1}{R_I^h}. \quad (5.9)$$

5.2.5 Robustness index calculation

Given a solution vector $\vec{T}^h$, whose elements are the optimal settings of the Volt/VAr devices at hour h , and assuming that the DG generation is kept fixed at the expected value at hour h , then it is possible to compute the robustness index associated with the solution vector $\vec{T}^h$.

Figure 16 exemplifies how to find the tolerable loading deviation boundaries, necessary for computing the robust margins (Equation 5.2 and Equation 5.1). The idea is to increase step by step the load from the reference k_{ref} until reaching the maximum loading (k_{max}) supported by the system without voltage violation. If the goal is to reach the minimum loading (k_{min}), the load is decreased from reference instead. The steps are accumulated in a variable Δ , which deviates the loading from the reference, resulting in a load value to be tested, k_{test} . For more accurate limits, first the mechanism finds a rough deviation Δ_{rough} that states the maximum deviation for a certain step accuracy. Then, a new search is performed from this rough deviation, but now with a refined step. After c_{max} iterations of this procedure, the limits are found with the specified precision. At the end, k_{min} and k_{max} are taken as the lower and upper robust limits, RL_l and RL_u , respectively.

Figure 16: Flowchart illustrating how to find load deviation limits (robust limits)

Figure 17 exemplifies some steps to find k_{max} . As the step size, added to Δ , exceeds the k_{max} in view, the new iteration refines the search by taking half the step size of the previous iteration. This procedure goes on until it finds k_{max} with the precision determined by the number of iterations (c_{max}) and the initial step size ($step_i$).

The maximum precision p_{max} for the robust limits values can be calculated by the following equation:

$$p_{max} = \frac{step_i}{2^{c_{max}}} \quad (5.10)$$

where $step_i$ is the initial step size and c_{max} is the number of iterations.

Figure 17: Example of finding k_{max} for $c_{max} = 5$

5.2.6 Robust parameters for PV

Similar to the robust definitions for load, it is possible to define some features to evaluate the capability of the control setting to face PV deviations from the expected values.

Given a vector $\vec{T}^h$, whose elements are the optimal settings of the Volt/VAr devices at hour h , and assuming that the loading is kept constant at the expected value at hour h , it is possible to verify the minimum limit of the PV output that such controls support the operation without voltage violation. This limit is called robust limit of PV (pv_{RL}^h). Figure 18 illustrates this value for the reference of PV (pv_{ref}^h), which is the forecast value used in the optimization.

Figure 18: Illustration of the limit supported by the control facing PV output deviation from the forecast

The extension from the reference PV output to the robust limit defines the robust

margin of PV (pv_{RM}^h) given by

$$pv_{RM}^h = pv_{ref}^h - pv_{RL}^h. \quad (5.11)$$

This robust margin establishes the robust range for PV output deviations from the forecast. That is, the control setting is capable of facing scenario realizations within this margin, keeping the voltage in the permitted limits. PV power output is reduced by cloud shadows passing over the PV array. Because of this, only downward deviations are considered in this definition.

Finally, the reliable robust margin of PV is defined as the allowable percentage of PV output deviation from the forecast that keeps the feasibility of the system operation with respect to voltage standards, given as

$$pv_{R\%}^h = \frac{pv_{RM}^h}{pv_{ref}^h} \times 100 [\%]. \quad (5.12)$$

For the calculation of the robust parameters for PV, the same strategies used for load ([subsection 5.2.5](#)) can be applied.

5.3 Single-objective VVO-based for snapshot CVR (Steady-CVR)

This formulation represents a conventional VVO-based CVR commonly considered in the literature. It will be used as a reference model to depict the effects of the uncontrollable variations of parameters according to the proposed robustness framework. Thus, having this basis for comparison, improved proposals may be developed.

5.3.1 Single-objective optimization problem formulation

The setting of the Volt/VAr equipment for optimal system operation is determined by the minimization of the following objective:

$$\text{minimize } f_{PI}^h \equiv P_{in}^h = P_{load}^h + P_{loss}^h \quad (5.13a)$$

$$\text{subject to } P_n^h = P_{Gn}^h - P_{Ln}^h, \quad (5.13b)$$

$$Q_n^h = Q_{Gn}^h - Q_{Ln}^h + Q_c^h, \quad (5.13c)$$

$$V_{min} \leq V_n^h \leq V_{max}, \quad (5.13d)$$

$$T_d^{min} \leq T_d^h \leq T_d^{max} \quad (5.13e)$$

where P_{in}^h is the active power intake in the distribution system from the substation at hour h , P_{load}^h is the the total active load power at hour h , P_{loss}^h is the total real power loss at hour h , P_n^h and Q_n^h are the active and reactive power of node n at hour h , P_{Gn}^h and Q_{Gn}^h

are the active and reactive power generation of node n at hour h , P_{Ln}^h and Q_{Ln}^h are the active and reactive power load of node n at hour h , Q_c^h is the amount of reactive power injected by capacitor c at hour h , V_n^h is the voltage of the node n at hour h , V_{min} and V_{max} are the acceptable voltage limits, T_d^h is the tap of the device d at hour h , and $T_{d,min}$ and $T_{d,max}$ are the tap position limits for the device d .

The objective function outlines the goal, per hour, designed to reduce the active power intake in the system f_{PI}^h . The constraints ensure the power balance, voltage limits, and the control devices' capacity.

5.3.2 Algorithm to solve the problem

The results in [subsubsection 4.5.2.2](#), from the previous chapter, showed that handling with constraints in VVO is not quite easy. So, a single-objective version of the constraint-domination operator ([subsection 3.2.4](#)) is suggested in the definition below to deal with constraints in the single-objective problem.

Definition 12: Given two vectors $\vec{u}$ and $\vec{v} \in \Omega$, where $\Omega \subseteq \Re^n$, it is said that $\vec{u}$ is constrained-better than $\vec{v}$ (denoted by $\vec{u} <_b \vec{v}$), if any of the following conditions is true:

- a) $\vec{u}$ is feasible and $\vec{v}$ is not;
- b) both are infeasible, but $\vec{u}$ has a small overall constraint violation;
- c) both are feasible, but $f(\vec{u}) < f(\vec{v})$.

[Algorithm 2](#) shows the pseudocode that assigns a rank for each solution according to the sorted position established by the constrained-better operator. The number of solutions in population P that are better than a given solution p will be the rank of this one. For example, rank equal to zero for p means that there is no better solution than p ; rank equal to one means that there is only one solution better than p ; and so on.

[Algorithm 3](#) shows the pseudocode for solving the single-objective snapshot CVR problem. First, the algorithm performs the population initialization and evaluation (line 1). Then, the evolution process begins by performing the classification of each individual (line 3) and keeping the k best individual (line 4). Two parents are selected by means of binary tournament (line 6). After the selection process, crossover and mutation operators are performed under repair ([subsection 4.4.2](#)) to generate a new offspring (lines 7-8). This offspring is evaluated and added to the offspring population Q (lines 9-10). When Q is filled, then the current population P will be updated with Q (line 12) and a new generation begins. At the end of all generations, P is ranked (line 14) and the best individual is selected (line 15). Finally, the robust parameters/metrics are computed for the best individual (line 16), which is the final solution.

The main characteristics of the implemented GA operators are:

Algorithm 2 Pseudocode to assign rank for P

```

1: procedure ASSIGN-RANK( $P$ )
2:   for each  $p \in P$  do
3:      $n_p = 0$ 
4:     for each  $q \in P$  do
5:       if  $q \neq p$  and  $q <_b p$  then ▷ If  $q$  is better than  $p$ ,
6:          $n_p = n_p + 1$  ▷ then increment the worsening counter of  $p$ .
7:       end if
8:     end for
9:      $p_{rank} = n_p$  ▷ It assigns the rank position of  $p$  within the sort.
10:  end for
11: end procedure

```

Algorithm 3 Pseudocode of the Steady-CVR method based on GA

```

1: Initialize population  $P$ . Evaluate  $P$ .  $g = 0$ 
2: while  $g \leq g_{max}$  do
3:    $assign\_rank(P)$ 
4:   keep  $k$ -best
5:   for  $i = 1$  to  $size(P) - k$  do
6:     Select two parents
7:     Crossover under repair
8:     Mutation under repair
9:     Evaluate new offspring
10:    Add to offspring population  $Q$ 
11:  end for
12:  Update  $P$  with  $Q$ .  $g = g + 1$ 
13: end while
14:  $assign\_rank(P)$ 
15: Select the best of  $P$ 
16: Compute robust parameters/metrics.

```

- a) **elitism:** based on the rank, the k best individuals are preserved for the next generation. It ensures the performance enhancement of the GA;
- b) **tournament selection:** p individuals are sampled from the population for a tournament. Based on the rank, the winner is chosen for reproduction;
- c) **flat crossover:** given a certain probability, it makes the exploitation (offspring lies between its parents) to generate the offspring $\vec{o}^h = (o_1^h, \dots, o_{N_D}^h)$ from the parents $\vec{p}^{1,h} = (p_1^{1,h}, \dots, p_{N_D}^{1,h})$ and $\vec{p}^{2,h} = (p_1^{2,h}, \dots, p_{N_D}^{2,h})$. Each tap o_i^h is a randomly chosen value within the interval:

$$o_i^h = random[\min(p_i^{1,h}, p_i^{2,h}), \max(p_i^{1,h}, p_i^{2,h})]; \quad (5.14)$$

- d) **random mutation:** given a certain probability, the operator replaces the genes of the children with random values between the specified upper and lower

bounds;

- e) **under repair**: it means that the repair influence f_{RI} attenuates the operator probability to happen (subsection 4.4.2).

5.4 Multi-objective VVO-based for robust snapshot CVR (Robust-CVR)

The aim of this formulation is to obtain solutions that are as good as possible in terms of CVR performance and, at the same time, are least sensitive to the load/DG variations. So, the problem is modeled as a MOP that deals with two main objectives: performance and robustness.

5.4.1 Multi-objective optimization problem formulation

The setting of the Volt/VAr equipment for optimal system operation is determined by the minimization of the following objectives:

$$\text{minimize } f_{PI}^h \equiv P_{in}^h = P_{load}^h + P_{loss}^h, \quad (5.15a)$$

$$f_{Sens}^h = 1/R_I^h \quad (5.15b)$$

$$\text{subject to } P_n^h = P_{Gn}^h - P_{Ln}^h, \quad (5.15c)$$

$$Q_n^h = Q_{Gn}^h - Q_{Ln}^h + Q_c^h, \quad (5.15d)$$

$$V_{min} \leq V_n^h \leq V_{max}, \quad (5.15e)$$

$$T_d^{min} \leq T_d^h \leq T_d^{max} \quad (5.15f)$$

where P_{in}^h is the active power intake in the distribution system from the substation at hour h , P_{load}^h is the the total active load power at hour h , P_{loss}^h is the total real power loss at hour h , f_{Sens}^h is the sensitivity of the Volt/VAr control for scenario changes at hour h , P_n^h and Q_n^h are the active and reactive power of node n at hour h , P_{Gn}^h and Q_{Gn}^h are the active and reactive power generation of node n at hour h , P_{Ln}^h and Q_{Ln}^h are the active and reactive power load of node n at hour h , Q_c^h is the amount of reactive power injected by capacitor c at hour h , V_n^h is the voltage of the node n at hour h , V_{min} and V_{max} are the acceptable voltage limits, T_d^h is the tap of the device d at hour h , and $T_{d,min}$ and $T_{d,max}$ are the tap position limits for the device d .

The objective functions outline the goals, per hour, designed to reduce the active power intake in the system f_{PI}^h and increase the robustness (modeled by the minimization of the sensitivity of the Volt/VAr control for scenario changes f_{Sens}^h). Thus, the solutions will accommodate a certain level of load/DG deviations without voltage violations and, at the same time, load demand and energy losses will be minimized. The constraints ensure the power balance, voltage limits, and the control devices' capacity.

5.4.2 Algorithm to solve the problem

NSGA-II is used to solve the proposed Volt/VAr multi-objective problem. The major adaptation from the standard algorithm (DEB et al., 2002) is related to the computation of the robust parameters/metrics before the evaluation of particles.

Algorithm 4 shows the pseudocode of the NSGA-II for solving the robust snapshot CVR problem. First, the algorithm performs the population initialization (line 1). The robust parameters/metrics are computed for each individual and the population evaluated (line 2). The evolution process begins by performing the fast non-dominated sort approach and computing the crowding-distance of the population (line 4). Then, two parents are selected by means of binary tournament (line 6). After the selection process, crossover and mutation operators under repair (subsection 4.4.2) are performed to generate a new offspring (line 7), followed by the computation of the robust parameters/metrics, and the evaluation of the new offspring (lines 8). This new offspring is added to the offspring population (line 9). When the offspring population is filled, the resulting union set between parents and offspring (line 11) is submitted to the fast non-dominated sort approach and crowding-distance computation (line 12). From this union set, the best ones are selected to update the parent population (line 13). Then, a new generation begins. At the end of all generations, the individuals in the first Front are the approximated Pareto optimal solutions (line 15). In essence, the robustness criteria R_I included into the Robust-CVR problem guides the EA to search in the robust regions of the search space.

Algorithm 4 Pseudocode of the Robust-CVR method based on NSGA-II

```

1: Initialize parent population  $P$ 
2: Compute robust parameters/metrics. Evaluate  $P$ .  $g = 0$ 
3: while  $g \leq g_{max}$  do
4:   fast-non-dominated-sort( $P$ ). crowding-distance-assignment( $P$ )
5:   for  $i = 1$  to size( $P$ ) do
6:     Select two parents
7:     Flat crossover and random mutation operators under repair
8:     Compute robust parameters/metrics. Evaluate new offspring
9:     Add to offspring population  $Q$ 
10:  end for
11:  Combine  $R = P \cup Q$ 
12:  fast-non-dominated-sort( $R$ ). crowding-distance-assignment( $R$ )
13:  Select the best of  $R$  to update  $P$ .  $g = g + 1$ 
14: end while
15: Report results in the first Front.

```

5.5 Results and Discussion

This section presents the results of applying the VVO-based CVR algorithms to the IEEE 123 node test feeder (KERSTING, 2001b). Variations in loading and distribution

generation are carried out to evaluate robustness of the Volt/VAr control solutions. It is important to note that the search space restriction method ([subsection 4.4.1](#)) is always used, although its results are not detailed from now on.

5.5.1 Configurations and scenarios

5.5.1.1 Base system, encoding/mapping, and decision variables

Base system

The distribution system used in the simulations is the IEEE 123 node test feeder ([KERSTING, 2001b](#)). No modification was made in the original system to preserve benchmark features. The one-line diagram of the IEEE 123 node test feeder can be seen in [Appendix A.1](#). It is worth mentioning that the IEEE 123 node test feeder was selected from the OpenDSS library, maintaining the network model exactly the same so that reproducibility of results may be achieved. This system presents a mix of constant impedance (24.36%), constant current (20.20%), and constant power (55.44%) loads. As part of the loads are voltage dependent, the CVR deployment may provide some benefits. Moreover, ZIP models can be used to represent the aggregated loads ([subsubsection 2.1.3.2](#)).

Problem encoding and mapping

The tap settings of the control devices — SVRs and SCs — are the decision variables of the optimization problem. The control configuration at a certain hour h is characterized by the vector $\vec{T}^h$ composed by individual taps T_d^h of each device d . The straightforward representation is:

$$\vec{x}^h \equiv \vec{T}^h = [T_1^h \quad T_2^h \quad \dots \quad T_d^h \quad \dots \quad T_{N_D}^h] \quad (5.16)$$

where N_D is the number of devices.

For voltage regulators, T_d means the tap number set by the optimization algorithm. It can represent one phase or three-phase voltage regulators.

Whereas, for capacitors, T_d means the number of capacitor modules switched on in the capacitor bank. Thus, the reactive power of each capacitor bank is given by:

$$Qsh_n = t_d \times Qsh_n^{mod} \quad (5.17)$$

where Qsh_n is the total reactive power injected at node n , t_d is the number of modules switched on in the capacitor bank located at node n , and Qsh_n^{mod} is the elementary reactive power of each module at node n .

The solution of the optimization problem is achieved through Python-based algorithms interfacing OpenDSS software, as described in [subsection 4.3.4](#). The EAs are

implemented through Python scripts that recurrently call the OpenDSS model to run power flow calculations. In EA terms, the individual is a decision vector that carries information related to the control variables — the tap settings of the control devices. Throughout EA process, the decision vector $\vec{x}^h$, encoded as integer values, evolves according to feasibility and performance outputs.

The Volt/VAr optimization problem is formulated as a mapping from the design space X , where $X \subset \mathbb{N}^{N_D}$ represents all possible discrete tap configurations of the N_D devices, into:

- a) the objective space $Y_1 \subset \mathbb{R}$, $f_o : X \rightarrow Y_1$, where $f_o(\vec{x}^h) = f_{PI}^h$ is the distribution system response for the single-objective problem;
- b) the objective space $Y_2 \subset \mathbb{R}^2$, $\vec{f}_o : X \rightarrow Y_2$, where $\vec{f}_o(\vec{x}^h) = [f_{PI}^h, f_{Sens}^h]$ is the distribution system response for the multi-objective problem;
- c) the constraint voltage violation space $C \subset \mathbb{N}$, $f_c : X \rightarrow C$, where $f_c(\vec{x}^h) = f_{VV}^h$ is the number of voltage violations on the system at hour h .

Decision variables

The optimization problem presents eight decision variables which are dealt as integer tap values by the algorithm. Such values are depicted as:

- a) **step voltage regulators:** the tap ratio is taken from 0.90 to 1.10 pu in steps of 0.00625 pu. Specifically,
 - SVR.1 is gang-operated (the taps change at the same time);
 - SVR.2 is an individual phase regulator at phase A;
 - SVR.3 has independent tap changing at phases A and C;
 - SVR.4 has independent tap changing at all phases;
- b) **switching shunt capacitor:** the reactive power is taken from 0 to 600 kvar in modules of 150 kvar. SC.1 has three-phase modules.

5.5.1.2 Parameters of the algorithms

[Table 8](#) describes the common parameters used in the implementation of both VVO-based CVR algorithms.

Table 8: Parameters of robustness index and repair process

EAs	Parameters and values		
Robustness index	$step_i$: 0.1	c_{max} : 8	p_{max} : 0.000390625
Repair process	α : 0.001	β : 1.0	rc_{max} : 1,000

The EAs parameters are shown in Table 9. They were empirically found according to the historical practices in the literature that reports high and low probability for crossover and mutation, respectively.

Table 9: EAs parameters

EAs	Population	Generation	Selection	Elitism	Crossover	Mutation
GA	40	100	$p = 2$	$k = 10$	90%	33%
NSGA-II	20	200	$p = 2$	—	90%	33%

5.5.1.3 Input conditions for VVO

The system must accommodate the connection of a distributed generator at bus 76, which is the best location for loss minimization according to Anwar and Pota (2011). A photovoltaic generation capacity of 1 MVA is considered with unity power factor.

The daily load curve was taken from Jardini et al. (2000) and the capacity factor of PV generation was selected from persistent clear sky condition of a typical day in Brazilian Northeast region (INPE, 2016). Both curves are presented throughout the results section and further detailed in Appendix A.2.

5.5.2 Robust operation

Now, the results of the VVO-based CVR algorithms are shown. The values of the Steady-CVR method are the average results considered by 20 runs of the algorithm. Those of the Robust-CVR method are the non-dominated optimal solutions found by 20 runs of the algorithm. PV generation is integrated into the system throughout the operation. The following nomenclatures are present in the graphics which describe the robust features:

- upper/lower robust limit (RL_u or RL_l):** is the maximum/minimum load that the control can handle without voltage issues;
- robustness area (RA):** is the area between the upper and lower limits. It comprises all scenarios that the control is able to operate without voltage issues;
- robust limit of PV (pv_{RL}):** is the minimum PV output that the control is able to handle with;
- robustness area of PV (pv_{RA}):** is the area between the expected PV output and the robust limit of PV. It comprises all PV scenarios that the control is able to operate without voltage issues;
- expected load (k_{ref}) and PV (pv_{ref}):** are the daily load profile and PV output. They are input to the VVO problem. Based on these expected curves, the coordination is elaborated, determining the schedule of the VVO devices.

5.5.2.1 Results for loading scenario changes

The following results are related to load deviations in relation to the load curve, while the PV generation keeps following its respective curve. In Figure 19–Figure 20, the robust limits RL_u and RL_l are analyzed. Initially, these robust parameters are computed from the optimal solution found for the Steady-CVR problem (Figure 19). Then, the Robust-CVR problem is solved and three distinct solutions are chosen (Figure 20(a)–Figure 20(c)). Different from the single-objective case (Steady-CVR), the multi-objective case (Robust-CVR) computes the robust parameters (RL_u and RL_l) during the optimization process, since they are incorporated into the optimization problem.

Figure 19 refers to the Steady-CVR algorithm, i.e., the optimization that considers only minimization of CVR goals. The upper limit of the permitted load is very close to the reference load, $RL_u^h \approx k_{ref}^h$. Therefore, there is no margin for loading increase, once this will cause voltage violation. Despite of the optimal CVR operation (shown later in 5.5.4.2), the control has not guaranteed robustness for unpredictable loading deviation from the reference (forecast). Because the reliable robust margin is minimum, this solution will be addressed as $RM_{R,min}$.

Figure 19: Robust margins of Steady-CVR: $RM_{R,min}$

We observed that conventional CVR aims to select taps that produce overall reduced voltage values, that is why any loading increase that causes voltage drop in the feeder will make some node voltages to have the voltage lower limit violated. The greatest contribution in this analysis is to highlight that conventional CVR works on the threshold of the feasibility.

The proposed Robust-CVR produces a set of non-dominated solutions. Thus, decision-making is required to select one of them. We will make use of the percentage of reliable robust margin $RM_{R\%}^h$ as a means of identifying user-preferred solutions. In detail, the solutions with the following specifications will be selected:

- a) $RM_{R,20\%}^h$: the solution with $RM_{R\%}^h$ equal to 20% or immediately higher;

- b) $RM_{R,40\%}^h$: the solution with $RM_{R\%}^h$ equal to 40% or immediately higher;
- c) $RM_{R,max}^h$: the solution with the maximum reliable robust margin.

Figure 20 shows the enlarged robustness area obtained by the proposed Robust-CVR method. The greater the reliable robust margin specification, the greater the resulting robustness area. In comparison with the Steady-CVR robustness area, the percentage of increase are 20.12%, 35.20%, and 126.21%, for the solutions $RM_{R,20\%}^h$ (Figure 20(a)), $RM_{R,40\%}^h$ (Figure 20(b)) and $RM_{R,max}^h$ (Figure 20(c)), respectively.

Improved robust upper and lower limits ensure quality of power supply for loading scenario changes. This means that the tap settings found by the Robust-CVR method are able to deal with either load increase or decrease and still keep the voltages within the allowed limits. In summary, the Robust-CVR can face greater load variations than the Steady-CVR method. This confirms the importance of incorporating the proposed robustness index into the Volt/VAr optimization problem.

Figure 20: Robust margins of Robust-CVR: (a) $RM_{R,20\%}^h$, (b) $RM_{R,40\%}^h$, and (c) $RM_{R,max}^h$

Figure 21 shows the percentage values of the reliable robust margin. The user-preferred solutions found by the Robust-CVR are capable of supporting much greater load deviations from the forecast than the Steady-CVR method. The idea behind specifying a percentage value is to ensure a certain tolerance for uncontrollable variations. In particular, Figure 21 confirms that the results of $RM_{R,20\%}$ ensures feasibility for at least 20% of load deviations and the results of $RM_{R,40\%}$, for at least 40%. In addition, $RM_{R,max}$ demonstrates the potential for reliable robustness increase, ranging from 61.60% to 100.00% along the day. The percentage of 100.00% means that, even if the load deviates completely, downward or upward, feasibility are ensured. It is important to highlight that the analysis made in Figure 19–Figure 21 concerns the voltage constraint satisfaction and not the performance of the system operation.

Figure 21: Percentage of the reliable robust margin $RM_{R\%}$

Table 10 shows the active power intake f_{PI} values (in MWh) of the solutions. Also, the relative percentage difference ($\Delta\%$) between the Robust-CVR solutions and the Steady-CVR solution is calculated. This table reveals that a compromise must be fulfilled so that robustness can be improved. The greater the robustness specification, the greater the active power intake demanded by the substation. However, the results demonstrate that, for a huge gain in robustness, it is only necessary to slightly increase the active power intake in the system. Although the Robust-CVR method demands more active power intake than the Steady-CVR, such increase represents small relative percentages. Specifically, these percentages of increase are in average 1.50%, 2.75%, and 8.21% for $RM_{R20\%}$, $RM_{R40\%}$, and $RM_{R,max}$ solutions, respectively, in a daily operation. These encouraging results reveal that it is possible to keep a good performance of the system operation control and, at the same time, make it robust feasible to uncertainty realizations of load.

Table 10: Comparative active power intake f_{PI} results

Hour	Steady-CVR		Robust-CVR				
	$RM_{R,min}$	$RM_{R,20\%}$		$RM_{R,40\%}$		$RM_{R,max}$	
	f_{PI} [MWh]	f_{PI} [MWh]	$\Delta\%$	f_{PI} [MWh]	$\Delta\%$	f_{PI} [MWh]	$\Delta\%$
1	0.904	0.914	1.08	0.919	1.66	0.986	9.03
2	0.949	0.954	0.54	0.959	1.09	1.028	8.37
3	1.016	1.023	0.73	1.031	1.52	1.102	8.50
4	0.958	0.963	0.50	0.971	1.32	1.042	8.78
5	0.961	0.966	0.57	0.974	1.39	1.042	8.48
6	0.982	0.987	0.53	0.997	1.53	1.068	8.81
7	0.825	0.829	0.49	0.834	1.09	0.900	9.02
8	1.158	1.172	1.18	1.182	2.10	1.262	8.96
9	2.274	2.325	2.21	2.359	3.72	2.438	7.19
10	2.086	2.133	2.29	2.167	3.93	2.247	7.76
11	1.999	2.052	2.61	2.084	4.22	2.175	8.78
12	2.092	2.149	2.73	2.188	4.58	2.264	8.23
13	0.694	0.712	2.57	0.729	5.05	0.815	17.47
14	2.011	2.061	2.49	2.101	4.44	2.187	8.76
15	2.304	2.362	2.51	2.410	4.57	2.481	7.67
16	2.539	2.597	2.31	2.638	3.91	2.710	6.74
17	2.716	2.784	2.49	2.816	3.65	2.894	6.53
18	2.662	2.702	1.48	2.734	2.69	2.796	5.03
19	2.191	2.228	1.68	2.251	2.74	2.326	6.16
20	2.035	2.063	1.39	2.089	2.67	2.172	6.73
21	2.008	2.035	1.36	2.060	2.61	2.144	6.77
22	1.471	1.489	1.18	1.506	2.35	1.578	7.25
23	1.114	1.119	0.47	1.132	1.58	1.199	7.65
24	0.989	0.994	0.52	1.004	1.52	1.073	8.42

Table 11 shows the robustness index R_I of the solutions. Also, the relative percentage difference ($\Delta\%$) between the Robust-CVR solutions and the Steady-CVR solution is calculated. As we have seen, R_I is the index used in the optimization process to perform comparison between solutions. It is notable that huge robustness gain is achieved for the Robust-CVR when compared with the Steady-CVR. The gain percentages are in the range of [171.53%, 8280.07%], [426.24%, 13509.35%], and [1193.06%, 17929.43%] for $RM_{R20\%}$, $RM_{R40\%}$, and $RM_{R,max}$ solutions, respectively, along the day. These gains correspond to

small relative percentages of increase of the active power intake in Table 10 (again, the average increase percentages are 1.50%, 2.75%, and 8.21%, respectively). So, huge gain in robustness index can be obtained from small increase of active power intake.

Table 11: Comparative robustness index R_I results

Hour	Steady-CVR	Robust-CVR					
	$RM_{R,min}$	$RM_{R,20\%}$		$RM_{R,40\%}$		$RM_{R,max}$	
	R_I [pu]	R_I [pu]	$\Delta\%$	R_I [pu]	$\Delta\%$	R_I [pu]	$\Delta\%$
1	0.019	0.612	3111.34	0.854	4380.59	1.936	10054.09
2	0.064	0.516	710.86	0.761	1095.88	1.933	2937.21
3	0.083	0.451	446.13	0.758	817.73	1.911	2212.39
4	0.099	0.492	397.58	0.750	659.33	1.932	1855.37
5	0.091	0.480	427.62	0.744	717.14	1.930	2021.05
6	0.084	0.432	415.12	0.809	865.01	1.928	2200.61
7	0.105	0.439	319.98	0.821	685.12	1.949	1764.25
8	0.054	0.475	771.76	0.773	1318.06	1.855	3305.55
9	0.010	0.397	3712.61	0.759	7183.66	1.109	10546.90
10	0.042	0.397	837.73	0.771	1722.04	1.063	2412.92
11	0.006	0.439	6772.06	0.756	11739.73	1.040	16186.41
12	0.051	0.406	690.77	0.740	1340.51	0.975	1798.62
13	0.033	0.409	1143.03	0.779	2264.94	1.693	5041.00
14	0.032	0.410	1173.12	0.744	2208.37	1.019	3060.74
15	0.020	0.407	1974.18	0.728	3609.75	0.943	4703.98
16	0.021	0.398	1813.65	0.719	3356.38	0.930	4369.81
17	0.005	0.453	8280.07	0.736	13509.35	0.975	17929.43
18	0.047	0.417	784.71	0.800	1599.90	1.162	2366.87
19	0.011	0.393	3384.40	0.781	6816.03	1.415	12439.08
20	0.014	0.404	2723.54	0.761	5216.01	1.508	10437.13
21	0.030	0.400	1253.03	0.792	2582.09	1.575	5230.87
22	0.010	0.500	4860.46	0.762	7459.19	1.776	17519.52
23	0.146	0.396	171.53	0.768	426.24	1.888	1193.06
24	0.059	0.414	595.82	0.791	1230.56	1.925	3137.55

Figure 22 shows this trade-off relation by putting active power intake (Figure 22(a)) and robustness index (Figure 22(b)) side by side via bar graphs. The proposed Robust-CVR presents CVR goals slightly bigger than the traditional Steady-CVR approach and, at the same time, it achieves a huge gain in robustness as mentioned before.

Figure 22: Performance versus robustness: (a) active power intake; (b) robustness index

5.5.2.2 Results for DG scenario changes

Now, the analysis is made to verify the robustness in the face of fluctuations on PV generation, while the loading keeps following the load curve. Of course, desirable solutions must provide a robust feasible control not only for uncertainties in the load demand, but also for uncertainties in the DG generation.

Figure 23 shows the limited capability of the Steady-CVR method to face the stochastic behavior of renewable-based DG. The robust limit is very close to the PV output, $pv_{RL}^h \approx pv_{ref}^h$. This reveals that small variations on the PV output are enough to cause power quality problems regarding voltage violation when the optimization considers only CVR goals. Therefore, the margin of operation is so tight that makes impracticable the operation when renewable-based DG is present in the system. By way of example, opaque clouds can cause reductions in the PV output by 50% to 80% when a large cloud is passing over the array (STEFFERUD; KLEISSL; SCHOENE, 2012).

Figure 23: PV robust margin of Steady-CVR. Solution: $RM_{R,min}$

On the other hand, Figure 24–Figure 26 show the enlarged robustness area obtained by the proposed Robust-CVR method. Robust-CVR provides robustness for the control to deal with a wide range of PV power fluctuations. The greater the reliable robust margin specification, the greater the resulting robustness area for PV. In relation to the Steady-CVR robustness area, the percentage of increase are 802.76%, 884.31%, and 911.31%, for the solutions $RM_{R,20\%}^h$, $RM_{R,40\%}^h$ and $R_{R,max}^h$, respectively.

Table 12 shows the results for the reliable robust margin of PV during the hours of PV generation. Again, the Steady-CVR is a non-robust solution. Over the course of a day of operation, it can present voltage violation for small deviations of PV output from the forecast. For example, at hour 11, only 1.60% of PV output variation is enough to cause this problem. Real-world CVR problems cannot take such poor control. Steady-CVR better supports PV variation only at the hours of small PV outputs (i.e., hours 8 and 18).

Figure 24: PV robust margin of Robust-CVR. Solution: $RM_{R,20\%}$ Figure 25: PV robust margin of Robust-CVR. Solution: $RM_{R,40\%}$ Figure 26: PV robust margin of Robust-CVR. Solution: $RM_{R,max}$

Table 12 also shows the huge reliable robust margin improvement of the Robust-CVR method. Whereas $pv_{R\%}$ ranges from 64.75% to 100.00% in the $RM_{R,20\%}$ solution, it ranges from 80.78% to 100.00% in the $RM_{R,40\%}$ solution. Further robustness is reached by $RM_{R,max}$ solution, which achieves 100.00% percentage of robust margin. These results mean that, in addition to support the stochastic behavior of PV generation due to many small clouds, these solutions can further tolerate complete covering or uncovering of the PV array by a large cloud in certain hours. Therefore, Robust-CVR ensures quality of power supply for PV scenario changes, keeping the voltages within the allowed limits.

Table 12: Comparative results for the reliable robust margin of PV ($pv_{R\%}$)

Hour	pv_{ref} [pu]	Steady-CVR	Robust-CVR		
		$RM_{R,min}$	$RM_{R,20\%}$	$RM_{R,40\%}$	$RM_{R,max}$
		$pv_{R\%}$ [%]	$pv_{R\%}$ [%]	$pv_{R\%}$ [%]	$pv_{R\%}$ [%]
8	0.134	43.32	100.00	100.00	100.00
9	0.475	5.33	100.00	100.00	100.00
10	0.756	14.49	100.00	100.00	100.00
11	0.918	1.60	100.00	100.00	100.00
12	0.987	16.22	64.75	100.00	100.00
13	1.000	6.60	77.19	80.78	100.00
14	0.970	9.08	100.00	100.00	100.00
15	0.874	7.38	77.50	100.00	100.00
16	0.675	10.73	100.00	100.00	100.00
17	0.366	2.47	100.00	100.00	100.00
18	0.044	100.00	100.00	100.00	100.00

Given these points, the trade-off principle between performance and robustness also happens for the DG uncertainties. A small increase in the CVR goals is required to achieve huge improvement in robustness to face PV fluctuations. Figure 27 proves this balance.

It is important to say that, although the robustness index R_I is formulated based on the loading variation characteristics, the robustness enhancement for PV fluctuations is a result directly related to the improvement of the R_I values. This confirms the effectiveness of the proposed robustness index as a comprehensive metric capable to model the robustness features of the Volt/VAr optimization.

Figure 27: Performance versus robustness for PV fluctuations: (a) active power intake; (b) reliable robustness margin

5.5.2.3 Approximated Pareto front

Finally, to illustrate that the Robust-CVR control reaches near optimal active power intake (f_{PI}) minimization, Figure 28 depicts the set of trade-off solutions at each hour of operation. Maximizing robustness means minimizing the sensitivity of the Volt/VAr control for scenario changes (Equation 5.9). In order to handle only minimization objectives, sensitivity index was considered instead of robustness. There are solutions very close to the optimal active power intake values, which were taken from the Steady-CVR method. These optimal f_{PI} are represented by dashed lines in each graph.

Figure 28: Trade-off solutions of the Robust-CVR

5.5.3 Robustness analysis

Monte Carlo sampling can be applied in order to check how the solution behaves in the face of forecast deviation. So, through Monte Carlo simulations, random daily scenarios of load demand and PV power generation are generated based on a normal distribution, in which the mean values are the load demand and PV output expectations and their standard deviations (σ_D and σ_{PV} , respectively) are given by three different test groups:

- a) Group 1: $\sigma_D = 1\%$ and $\sigma_{PV} = 5\%$;
- b) Group 2: $\sigma_D = 2\%$ and $\sigma_{PV} = 10\%$;
- c) Group 3: $\sigma_D = 4\%$ and $\sigma_{PV} = 20\%$.

For each group, 500 daily prediction scenarios of hourly load demands and PV outputs are randomly generated under the normal distribution and then this number is reduced to 100 by employing the simultaneous backward reduction algorithm (HEITSCH; RÖMISCH, 2003; WANG et al., 2014).

5.5.3.1 Comparison of the daily voltage violations

Table 13 shows the number of daily voltage violations (Σ_{vv}) that resulted from the operation of the system when the Steady-CVR and Robust-CVR solutions are applied to the test groups of scenario changes. To verify the impact of PV fluctuations, two conditions are further tested which are labeled by:

- a) D: only load demand realizations are considered; PV outputs are preserved equal to the expectation values;
- b) D-PV: the realizations are carried out for both load demands and PV outputs.

From all scenarios, it is possible to verify the minimum (Min) and maximum (Max) values of Σ_{vv} and, also, the average (Avg) of Σ_{vv} for all scenarios.

Steady-CVR is much less robust to the variation in load/DG variables. From small to large uncertainties, Steady-CVR solution violates the permitted voltage limits. As the uncertainties increase, the Σ_{vv} measures (Min, Avg and Max) clearly increase. Moreover, these measures are intensified when the stochastic behavior of the PV generation is considered, in addition to that of the load.

The Robust-CVR solutions are very robust to the variation in load/DG variables. Table 13 shows that only the $RM_{R,20\%}$ solution presents voltage violation and this happen only when it faces the worst group of scenario changes, the one which models heavy uncertainties (Group 3).

Table 13: Number of daily voltage violations

		Steady-CVR		Robust-CVR					
σ_D, σ_{PV}	Σ_{vv}	$RM_{R,min}$		$RM_{R,20\%}$		$RM_{R,40\%}$		$RM_{R,max}$	
		D	D-PV	D	D-PV	D	D-PV	D	D-PV
1%, 5%	Min	3	16	0	0	0	0	0	0
	Avg	30.7	46.5	0.0	0.0	0.0	0.0	0.0	0.0
	Max	63	88	0	0	0	0	0	0
2%, 10%	Min	5	30	0	0	0	0	0	0
	Avg	70.1	108.5	0.0	0.0	0.0	0.0	0.0	0.0
	Max	171	253	0	0	0	0	0	0
4%, 20%	Min	40	78	0	0	0	0	0	0
	Avg	204.2	310.1	7.4	8.3	0.0	0.0	0.0	0.0
	Max	521	668	84	84	0	0	0	0

Table 14 shows the rate of infeasible daily scenarios (IDS_{rate}), a metric to express the percentage of scenarios with voltage issues. Steady-CVR solution produces voltage violation in 100% of the scenarios for all test groups. As these high rates happen in all tests, Steady-CVR method proves to be impractical in real-world CVR problems. On the other hand, Robust-CVR solutions are predominantly feasible in the face of the various uncertainty scales. Among them, only the $RM_{R,20\%}$ solution has $IDS_{rate} > 0\%$. But this happen before Group 3, the one which models heavy uncertainties. Apart from this condition, the other results are $IDS_{rate} = 0\%$.

Table 14: Rate of infeasible daily scenarios

		Steady-CVR		Robust-CVR					
σ_D, σ_{PV}	IDS_{rate}	$RM_{R,min}$		$RM_{R,20\%}$		$RM_{R,40\%}$		$RM_{R,max}$	
		D	D-PV	D	D-PV	D	D-PV	D	D-PV
1%, 5%	[%]	100	100	0	0	0	0	0	0
2%, 10%	[%]	100	100	0	0	0	0	0	0
4%, 20%	[%]	100	100	39	44	0	0	0	0

Therefore, although the stochastic behavior of load/DG influences the feasibility of the system operation, it is possible to design a control much immune to these uncertainties. The Robust-CVR method demonstrated this enhancement. Among Robust-CVR solutions, $RM_{R,20\%}$ is a promising solution for representing a good balance between performance and robustness.

5.5.3.2 Amount of time with voltage violations

The histograms in Figure 29–Figure 31 show the amount of time τ_{vv} in which voltage violations occur during the day and the percentage rate δ_τ of scenarios where such a value occurs. To clarify, the voltage violation may occur during τ_{vv} hours of the daily system operation in $\delta_\tau\%$ of the scenarios.

These figures are related to the Steady-CVR solution facing the test groups (1, 2 and 3, respectively). Also, each figure includes the condition D in subplot (a) and D-PV in subplot (b). To better compare the histograms, a Gaussian peak model can be used to express the fitting data.

Although infeasibility is present in all daily scenarios, it does not happen all day. This stochastic behavior challenges any coordinated control design. As the variability increases (from Group 1 to 3 in Figure 29–Figure 31), more hours of the day operation are spent with voltage regulation issues. The fitting Gaussian function proves this pattern by increasing the mean value μ .

Moreover, in the same test group, if the conditions D, in subplot (a), and D-PV, in subplot (b), are compared to each other, the fitting Gaussian function has an increase in the mean value μ . This effect confirms that the PV's stochastic behavior has a great influence on the feasibility of the solution. In summary, the presence of DG tends to affect the feasibility of the system operation in two aspects: 1) increasing the number of daily voltage violations and 2) increasing the number of hours with voltage violations.

Figure 29: Histogram of the amount of time with voltage violations. Group 1: $\sigma_D = 1\%$, $\sigma_{PV} = 5\%$

Figure 30: Histogram of the amount of time with voltage violations. Group 2: $\sigma_D = 2\%$, $\sigma_{PV} = 10\%$

Figure 31: Histogram of the amount of time with voltage violations. Group 3: $\sigma_D = 4\%$, $\sigma_{PV} = 20\%$

Therefore, the solution of the single-objective VVO-based snapshot CVR, regarded as a conventional method, is very sensitive against the uncertainties, i.e., it is a non-robust control solution. Although it does not adequately represent real-world CVR problems, this formulation is commonly used in the literature (JHA et al., 2019; GUTIERREZ-LAGOS; OCHOA, 2019).

5.5.4 CVR analysis

5.5.4.1 CVR effectiveness

CVR is accomplished by lowering voltages on the distribution system. So, in order to analyze the effectiveness that CVR is implemented, a correlation between average voltage and active power intake is made. For this, the Pearson's correlation coefficient is calculated in order to evaluate the strength of the linear relationship between these two variables.

Table 15 and Table 16 show the correlations between average voltage and active power intake throughout the evolution process for each hour. The first table refers to the Steady-CVR method, whereas the second one, to the Robust-CVR method. The results are taken by the average of the population results after 20 runs of the algorithms. Also, the first generations (three and two, respectively) were not considered in order to mitigate the effects of the initial conditions and initial infeasibility. The results show a strong correlation between the two variables which means that the CVR is effectively accomplished.

Table 15: Correlation coefficient between voltage and power intake (Steady-CVR)

Hour	Correlation	Hour	Correlation	Hour	Correlation
1	0.9861	9	0.9866	17	0.9915
2	0.9892	10	0.9889	18	0.9879
3	0.991	11	0.9902	19	0.9849
4	0.9916	12	0.9908	20	0.9871
5	0.9906	13	0.9885	21	0.9852
6	0.9923	14	0.992	22	0.9873
7	0.9913	15	0.9875	23	0.9911
8	0.9894	16	0.9921	24	0.9913

Figure 32 and Figure 33 show the scatter plots of the two variables for all hours. The first figure refers to the Steady-CVR method, whereas the second one, to the Robust-CVR method. The normalized data points have a well-defined increasing trend, confirming the strong positive correlation between average voltage and active power intake — lower voltages correspond to lower active power intake on the system.

Table 16: Correlation coefficient between voltage and power intake (Robust-CVR)

Hour	Correlation	Hour	Correlation	Hour	Correlation
1	0.9883	9	0.9894	17	0.9954
2	0.9714	10	0.9962	18	0.9958
3	0.9798	11	0.9853	19	0.992
4	0.974	12	0.9941	20	0.9921
5	0.9895	13	0.9708	21	0.9811
6	0.9803	14	0.9948	22	0.972
7	0.9787	15	0.992	23	0.9846
8	0.9857	16	0.9961	24	0.9849

Figure 32: Normalized scatter plot of the average voltage and active power intake (Steady-CVR method)

Figure 33: Normalized scatter plot of the average voltage and active power intake (Robust-CVR method)

Therefore, the relationship between average voltage and active power intake is strong. This demonstrates that the CVR model employed in this research (Equation 5.13a and Equation 5.15a) is effective, capturing the principle of the CVR operation.

5.5.4.2 Daily energy savings

The active power intake in the system has been used as a way to pursue energy savings by voltage reductions. Table 17 shows the capability of the VVO-based CVR in reducing daily energy consumption. The conventional voltage regulation (Conv-VR) — which automatically changes the tap settings to correct voltage violation (no optimization in this case) — is considered as the base case of energy consumption. Appendix B details the parameters of Conv-VR. The term $\Delta\%$ means the percentage of energy reduction in relation to the base case.

The Steady-CVR solution provides the greatest energy savings, 7.00% in comparison with the case base. Because its formulation has only this goal to optimize, we can address the Steady-CVR energy consumption as the optimal value (i.e., the best value).

The intermediate Robust-CVR solutions ($RM_{R,20\%}$ and $RM_{R,40\%}$) contributed with energy consumption reduction. Of course, the trade-off requires reducing energy savings to increase robustness. Whereas, the most robust solution ($RM_{R,max}$) could not obtain energy savings. This leads us to consider robust intermediate solutions. It is the case of the $RM_{R,20\%}$ solution which produces considerable energy savings (i.e., close to the optimal value) and, at the same time, it has an efficient robust margin to face a large scale of uncertainties.

Table 17: Comparative daily energy savings [MWh]

Conv-VR		Steady-CVR		Robust-CVR					
Base		$RM_{R,min}$		$RM_{R,20\%}$		$RM_{R,40\%}$		$RM_{R,max}$	
MWh		MWh	$\Delta\%$	MWh	$\Delta\%$	MWh	$\Delta\%$	MWh	$\Delta\%$
41.870		38.939	-7.00	39.613	-5.39	40.135	-4.14	41.930	0.14

Finally, the Robust VVO-based CVR method with intermediate degree of robustness ($RM_{R,20\%}$ and $RM_{R,40\%}$) fulfilled the CVR effectiveness by reducing voltages on the system. Table 18 shows the daily average voltage as a way of visualizing this reduction. As $RM_{R,max}$ solution presented higher levels of voltage, we can conclude that there is a limit for improving the robustness that guarantees the functioning of the CVR. In other words, very robust solutions may not be energy saving solutions. This clear trade-off between performance and robustness confirms once more the effectiveness of modeling such problem as a MOP.

Table 18: Comparative daily average voltage [V]

Conv-VR		Steady-CVR		Robust-CVR					
Base		$RM_{R,min}$		$RM_{R,20\%}$		$RM_{R,40\%}$		$RM_{R,max}$	
V		V	$\Delta\%$	V	$\Delta\%$	V	$\Delta\%$	V	$\Delta\%$
1.015		0.943	-7.12	0.950	-6.44	0.958	-5.60	1.016	0.11

5.6 Concluding remarks

This chapter has revealed that conventional CVR methods based on VVO have a significant drawback from the standpoint of scenario uncertainties. The optimal CVR solutions lie on the boundary of the feasible domain, making them quite sensitive to variable perturbations. Any increase in loading (or diminishing in DG) can produce power quality issues regarding the voltage standard limits. This is an unexpected result for many works that have been solving this problem in such a way. As the scale of scenario changes increases, the problem becomes bigger. In particular, the stochastic behavior of RES-based DG damages the feasibility of the control solution by increasing the number of nodes with voltage violations and increasing the amount of time with such issues.

To address the uncertainties of electrical demand and photovoltaic generation, several parameters and metrics were proposed to assess the robust feasibility of voltage constraints. The resulting framework can be used to investigate the ability of the scheduled control to face the stochastic nature of uncertainties and thus compare different VVO solutions from the perspective of robustness. The greatest advantages of these parameters/metrics are that they do not require a presumed probability distribution of the uncontrollable variables or parameters related to probability models; nor they need evaluating large numbers of scenarios to approximate the performance of the solution against a variety of uncertainty realizations.

In addition, the robustness framework was incorporated into the VVO-based CVR formulation through the multi-objective optimization problem — method named as Robust-CVR — to ensure power quality supply, even under diverse realizations of load/PV uncertainties. The results demonstrated the balance between performance and robustness. By slightly increasing the active power intake demand in the substation, it is possible to reach huge gains in robustness. This advantageous trade-off can ensure a robust control along with better energy savings than conventional voltage regulation methods. As the Robust-CVR method gives a set of solutions, decision-making was carried out based on a percentage metric which identifies user-preferred level of robustness among the solutions.

The results of this chapter encourage to further investigate the effects of improving the robustness of the system operation, but now focusing on the economic aspect. This is the subject of the following chapter. Finally, it is important to mention that robust

solutions have also been addressed in the literature as flexible solutions due to their ability to operate in dynamic environments ([JENSEN, 2003](#)). In real-world applications, a robust or flexible solution may be more valuable than an optimal solution that does not perform well when facing scenario changes. So, this means to design Volt/VAr control prepared for future events, which are often difficult to predict accurately.

6 COST ANALYSIS OF ROBUST VVO-BASED CVR

In Chapter 5 the Volt/VAr control was formulated as a multi-objective robust design optimization, in which the major purpose was to maximize energy savings through CVR procedure under stochastic environment. Now that a consistent robustness framework has been developed, it is possible to go further towards costs examination. Chapter 4 proposed the inclusion of the tap-changing costs into the operating costs. Besides the financial benefits, distribution operator seeks for more efficient utilization of assets (MADRIGAL; ULUSKI, 2015). So, focusing on studying the cost estimation in improving robustness, this chapter attempts to analyze the relation between the operating costs degradation and the design of robust solutions. Findings of this thesis have identified that the research literature lacks studies of the costs associated with robustness improvement.

6.1 Introduction

It is crucial to design robust Volt/VAr control to guarantee the reliable power supply of distribution systems under different sources of uncertainties, like those from renewable resources and load demand. But, working under realistic operating conditions can be a difficult and, consequently, costly task. So, the costs involved in dealing with these uncertainties must be investigated.

Initially, this chapter proposes a way of estimating the robustness costs. Then, comparisons are made by considering four different methods. At the end, the solutions of all methods are submitted to robustness analyses through Monte Carlo simulations, followed by CVR effectiveness investigation.

A great advantage of the robustness framework developed in this thesis is that it provides metrics for both objective function and decision making. Based on this, the proposed method, called Robust-DM, in this chapter incorporates the robustness index as an additional objective function to be minimized and, among the multiple candidate solutions, the one that meets the specified degree of robustness is chosen. Throughout the analyses, the Robust-DM is validated as a promising advanced method for smart grid applications capable of finding robust and cost-effective CVR solutions on a real-time scale.

6.2 Robustness costs

The proposed manner to estimate the robustness costs is based on calculating the difference between the operating costs resulted from the robustness improvement and the optimal operating costs. This estimation can be expressed as:

$$RC = OC_{robust} - OC_{optimal} \quad (6.1)$$

$$OC_{I\%} = \frac{RC}{OC_{optimal}} \times 100 [\%] \quad (6.2)$$

where RC is the robustness cost, OC_{robust} is the operating cost of the robust solution, $OC_{optimal}$ is the optimal operating cost (the OC is the objective function minimized in a SOP), and $OC_{I\%}$ is the percentage increase in operating costs of the robust solution.

6.3 Methods for comparison

The case study is conducted to demonstrate the impact of the robust VVO-based CVR on the economics. For this, four methods are implemented for comparison purposes. They are:

- a) **Conv-VR:** it performs a conventional voltage regulation. The Conv-VR gives traditional values of operating costs;
- b) **Optimal-OC:** it models a single-objective optimization problem focusing only on reducing the operating costs. Therefore, Optimal-OC is a reference for optimal values of operating costs;
- c) **Worst-case-OC:** it seeks the optimal operating costs under worst case scenarios. Thus, Worst-case-OC is a representative method for robust optimization in literature, giving a reference robust optimal solution;
- d) **Robust-DM:** it models a multi-objective optimization problem making a balance between operating costs and robustness objectives. Then, decision is made based on a chosen level of robustness. Robust-DM incorporates the proposed robust parameters/metrics ([section 5.2](#)) into the optimization.

The VVO-based CVR methods must fulfill their duty of producing energy and cost savings. To estimate these values, the Conv-VR solution is taken as a reference, since it is an effective and widely applied voltage regulation method. The Optimal-OC method searches for the near-minimal OC , which may not be implementable in real conditions. But, this ideal solution can be assigned as the $OC_{optimal}$ in [Equation 6.1](#) so that the robustness costs of robust methods may be computed. The Worst-case-OC is a benchmark method whose solution is a goal to be pursued in terms of costs and robustness. Thus, in summary, a robust-economic solution must: 1) produce energy and cost savings in comparison with the Conv-VR; 2) achieve better robustness than the Optimal-OC; 3) pursue costs and robustness close to the Worst-case-OC. In addition, due to the smart grid context, we also have the following demand: 4) the solution must have a low computational time for real-time applications. Aiming to meet all these requirements, this thesis has proposed the Robust-DM method in the present chapter.

Before detailing each method, it is important to identify some design measures adopted:

- a) A simplified SES-VVO (section 4.4) is utilized in the Optimal-OC, Worst-case-OC, and Robust-DM methods. Specifically, the following proposed mechanisms are employed: Restrict Search Space (subsection 4.4.1), Repair Process (subsection 4.4.2), and HTP (subsection 4.4.3).
- b) The operating costs are computed hourly, requiring the previous tap decision. Therefore, for all methods, the current solution found is taken as the previous tap decision for the next hour. This strategy is equivalent to the DM-SES-VVO with $\Delta = 0$ (subsubsection 4.4.6.2).
- c) The robust parameters/metrics (section 5.2) are applied at the final solutions of Conv-VR, Optimal-OC, and Worst-case-OC methods. On the other hand, these parameters/metrics are incorporated into the proposed Robust-DM method, which uses them throughout the optimization process;
- d) To provide a fair cost comparison, the initial previous tap settings T_d^0 are the same for all methods. These tap settings can be interpreted as the last tap decision of the previous day operation. The T_d^0 is taken from the Steady-CVR method (section 5.3);
- e) The proposed robust parameters/metrics in section 5.2 are calculated hourly. That is why the complexity of time-coupling is reduced to the twofold input: previous control and actual data.

6.3.1 Conventional voltage regulation (Conv-VR)

The conventional voltage regulation (Conv-VR) automatically changes the tap settings of the SVRs to accomplish the automatic control by LDC as shortly described in subsubsection 2.2.1.2 (no optimization in this case), whereas the reactive power of the capacitors are considered fixed. Appendix B details the parameters of Conv-VR. A control that only react to compensate the voltage drop on the feeder can be used to estimate a traditional operating costs. For this reason, the Conv-VR is regarded as a base case.

6.3.2 Optimal operating costs (Optimal-OC)

The following formulation seeks to find the optimal operating costs (Optimal-OC), which represents the economic solution reference. Having this reference, it is possible to study the impacts on the operating costs caused by the robustness improvement.

Optimal-OC formulation

The setting of the Volt/VAr equipment for optimal system operation is determined by the minimization of the following objective:

$$\text{minimize } f_o^h \equiv OC^h = C_{PI}^h + C_{SO}^h \quad (6.3a)$$

$$\text{subject to } P_n^h = P_{Gn}^h - P_{Ln}^h, \quad (6.3b)$$

$$Q_n^h = Q_{Gn}^h - Q_{Ln}^h + Q_c^h, \quad (6.3c)$$

$$V_{min} \leq V_n^h \leq V_{max}, \quad (6.3d)$$

$$T_d^{min} \leq T_d^h \leq T_d^{max} \quad (6.3e)$$

where OC^h is the operating cost (see Equation 4.12) at hour h , C_{PI}^h is the cost related to the active power intake into the distribution system at hour h , C_{SO}^h is the cost related to the tap changes from hour $h - 1$ to h , P_n^h and Q_n^h are the active and reactive power of node n at hour h , P_{Gn}^h and Q_{Gn}^h are the active and reactive power generation of node n at hour h , P_{Ln}^h and Q_{Ln}^h are the active and reactive power load of node n at hour h , Q_c^h is the amount of reactive power injected by capacitor c at hour h , V_n^h is the voltage of the node n at hour h , V_{min} and V_{max} are the acceptable voltage limits, T_d^h is the tap for each Volt/VAR device d at hour h , and $T_{d,min}$ and $T_{d,max}$ are the tap position limits for the device d .

The objective function outlines the goal, per hour, designed to reduce the operating costs (OC^h). The constraints ensure the power balance, voltage limits, and the control devices' capacity.

Optimal-OC method

The method to solve the Optimal-OC problem is similar to the method in subsection 5.3.2, proposed to solve the Steady-CVR. The main differences are related to the need of providing a previous tap T_d^{h-1} and that the random mutation is replaced by a multi-mutation strategy which selects one of three mutation operators (random, non-uniform, and the proposed HTP (subsection 4.4.3)) with equal chance to happen. The multi-mutation strategy can be given by:

$$\text{mutation operator} = \text{random}([\text{random}, \text{non-uniform}, \text{HTP}]). \quad (6.4)$$

Algorithm 5 shows the pseudocode for solving the hourly Optimal-OC problem, which is a SOP. First, it is necessary to identify the previous tap settings T_d^{h-1} to compute the costs related to tap changes at the current hour (line 1). These tap settings are taken from the solution found in the previous hour. Next, the algorithm performs the population initialization and evaluation (line 2). Then, the evolution process begins by performing the classification of each individual (line 4) and keeping the k best individual (line 5). Two parents are selected by means of binary tournament (line 7). After the selection process, crossover and multi-mutation operators are performed under repair (subsection 4.4.2) to

generate a new offspring (lines 8-9). This offspring is evaluated and added to the offspring population Q (lines 10-11). When Q is filled, then the current population P will be updated with Q (line 13) and a new generation begins. At the end of all generations, P is ranked (line 15) and the best individual is selected (line 16). Finally, the robust parameters/metrics (section 5.2) are computed for the best individual (line 17), which is the final solution.

Algorithm 5 Pseudocode of the Optimal-OC method based on GA

```

1: Find previous tap  $T_d^{h-1}$ 
2: Initialize population  $P$ . Evaluate  $P$ .  $g = 0$ 
3: while  $g \leq g_{max}$  do
4:   assign-rank( $P$ )
5:   keep  $k$ -best
6:   for  $i = 1$  to  $\text{size}(P) - k$  do
7:     Select two parents
8:     Flat crossover under repair
9:     Multi-mutation under repair
10:    Evaluate new offspring
11:    Add to offspring population  $Q$ 
12:  end for
13:  Update  $P$  with  $Q$ .  $g = g + 1$ 
14: end while
15: assign-rank( $P$ )
16: Select the best of  $P$ 
17: Compute robust parameters/metrics

```

6.3.3 Worst-case operating costs (Worst-case-OC)

A classical way to design robust solutions is by considering the worst case scenarios in the optimization. Specifically, the minimax criterion can be applied to optimize the objective function in the worst case over a set of possible scenarios. But, instead of considering a predefined fixed set of scenarios before optimization (normally seen in robust optimization), in this method the scenarios are created dynamically throughout the evolution process like in Roberts et al. (2018). That is, during the offspring evaluation process, the variables under uncertainty are perturbed to create different scenarios, among which the worst-case solution is chosen (SOARES et al., 2017).

Worst-case-OC formulation

The minimum operating costs problem under the worst-case scenario of load/DG uncertainty can be hourly solved by the minimax method as follows:

$$\begin{aligned}
 & \min_{\vec{x} \in X} \max_{\xi \in \Xi} f_o(\vec{x}, \xi) \\
 & \text{s.t. constraints 6.3b--6.3e}
 \end{aligned} \tag{6.5}$$

where $f_o(\vec{x}, \xi)$ is the objective function modeled by the *OC* in Equation 6.3a, $\vec{x}$ is the n -dimensional vector of decision variables, X is the set of candidate solutions, ξ is the vector of random variables (load/DG uncertainty), and Ξ is the set of all possible scenarios.

Therefore, the problem is to find a robust solution that has the best worst-case performance. In other words, Equation 6.5 aims at minimizing (over all solutions) the maximum (over all scenarios) performance. Despite being effective in improving system robustness, this approach is considered overly conservative.

Worst-case-OC method

The probabilistic optimization proposed in Roberts et al. (2018) was applied to solve the Worst-case-OC problem. For this, the Algorithm 5 was accordingly modified in the evaluation step (line 10). Before the evaluation of each new offspring, the uncertainty scenarios are generated — a total of N_{samp} samples for hourly load/DG scenarios are generated using the Gaussian distribution function. So, the current offspring ($\vec{o}$) is simulated N_{samp} times under the uncertainty scenarios resulting in the following vector of *OC* results:

$$\overrightarrow{OC}(\vec{o}, \xi) = [OC(\vec{o}, \xi_1), OC(\vec{o}, \xi_2), \dots, OC(\vec{o}, \xi_{N_{samp}})] \quad (6.6)$$

where $\xi_1, \xi_2, \dots, \xi_{N_{samp}}$ are the random scenarios of hourly load/DG sampled for the current offspring ($\vec{o}$).

At this point, the minimax method presented in Equation 6.5 is applied to obtain a deterministic value from the vector of *OC* results derived from the simulations. This means to take the worst-case performance result to be addressed as the fitness of the offspring:

$$f_o(\vec{o}, \xi_{wc}) \equiv OC(\vec{o}, \xi_{wc}) = \max[OC(\vec{o}, \xi_1), OC(\vec{o}, \xi_2), \dots, OC(\vec{o}, \xi_{N_{samp}})] \quad (6.7)$$

where ξ_{wc} is the worst-case scenario for $\vec{o}$.

Algorithm 6 illustrates the process of creating a new offspring. First, two parents are selected by binary tournament. Then, the repair process loop (subsection 4.4.2) begins. Within the repair process, the probabilities of crossover and mutation are updated according to the repair influence value f_{RI} . After this, the offspring is generated by using flat crossover and multi-mutation (Equation 6.4) operators. Then, random scenarios of load/DG are created and the offspring is evaluated under these scenarios. Thus, the offspring fitness is assigned with the worst-case performance. If the voltage violation (Equation 4.5) of the offspring is lower or equal to its parents under worst-case scenario, then the process of creating a new offspring is finished. Otherwise, the repair counter is increased, starting a new iteration of the repair process.

Algorithm 6 Pseudocode to create a new offspring under random scenarios

```

1: Select parents  $p_1, p_2$ 
2:  $rc = 0$  ▷ initialize repair counter
3: while  $rc < rc_{max}$  do ▷ repair process loop
4:   Compute  $f_{RI}(rc)$  to update crossover/mutation probabilities
5:   Generate offspring  $\vec{o}$  using crossover and multi-mutation operators
6:   Generate  $N_{smp}$  scenarios:  $\xi_1, \xi_2, \dots, \xi_{N_{smp}}$ 
7:   Evaluate  $\vec{o}$  under all set of scenarios (Equation 6.6)
8:   Find  $\xi_{wc}$ . Assign fitness with the worst-case performance (Equation 6.7)
9:   if  $f_{VV}(\vec{o}, \xi_{wc}) \leq \min[f_{VV}(\vec{p}_1, \xi_{wc}), f_{VV}(\vec{p}_2, \xi_{wc})]$  then
10:    New offspring is ready. Break
11:   else
12:     $rc = rc + 1$  ▷ increase repair counter
13:   end if
14: end while
15: Add  $\vec{o}$  to offspring population  $Q$ 

```

The vectors of random variables $(\xi_1, \xi_2, \dots, \xi_{N_{smp}})$, uncertainty realizations of load/DG, are generated based on a normal distribution, in which the mean values are the load demand and PV output expectations and their standard deviations are given by $\sigma_D = 2\%$ and $\sigma_{PV} = 10\%$, respectively.

6.3.4 Robust decision making (Robust-DM)

The aim of this formulation is to obtain solutions that are as good as possible in terms of operating costs savings and, at the same time, are least sensitive to the parameter variations of load/DG. So, the problem is modeled as a MOP, dealing with two main objectives: the operating costs OC , derived from Chapter 4, and the robustness index R_I , proposed in Chapter 5. Furthermore, it is necessary to select one solution from the set of non-dominated solutions. To make this decision, the percentage of reliable robust margin $RM_{R\%}$, metric proposed in Chapter 5, is applied. More details are below.

Robust-DM formulation

The robust setting of the Volt/VAr equipment for optimal system operation is determined by the minimization of the following objectives:

$$\text{minimize} \quad f_{OC}^h \equiv OC^h = C_{PI}^h + C_{SO}^h, \quad (6.8a)$$

$$f_{Sens}^h = 1/R^h \quad (6.8b)$$

subject to constraints 6.3b–6.3e

where OC^h is the operating cost (see Equation 4.12) at hour h , given by the sum of the costs related to the active power intake into the distribution system at hour h (C_{PI}^h)

and the costs related to the tap changes from hour $h - 1$ to h (C_{SO}^h), and f_{Sens}^h is the sensitivity index (subsection 5.2.4) at hour h , given by the inverse of the robustness index R_I^h (subsection 5.2.2).

The objective functions outline the goals, per hour, designed to reduce the operating costs of the system under realistic operating conditions — the presence of uncertainties in the input variables related to solar irradiance and load demand. The robustness improvement is modeled by the minimization of the sensitivity of the Volt/VAr control for scenario changes.

Robust-DM method

The method to solve the Robust-DM problem is similar to the method in subsection 5.4.2, proposed to solve the Robust-CVR. The main difference is that the random mutation is replaced by the multi-mutation strategy (Equation 6.4). Moreover, it is necessary to provide the previous tap T_d^{h-1} to compute the costs related to tap changes at the current hour and, also, to make a decision based on the reliable robustness margin $RM_{R\%}$ at the end of the evolution.

Algorithm 7 shows the pseudocode of the method for solving the Robust-DM problem. First, it is necessary to identify the previous tap settings T_d^{h-1} to compute the costs related to tap changes at the current hour (line 1). Next, the algorithm performs the population initialization (line 2). The robust parameters/metrics (section 5.2) are computed for each individual and the population are evaluated (line 3). The evolution process begins by performing the fast non-dominated sort approach and computing the crowding-distance of the population (line 5). Then, two parents are selected by means of binary tournament (line 7). After the selection process, crossover and multi-mutation (Equation 6.4) operators are performed under repair (subsection 4.4.2) to generate a new offspring (line 8), followed by the computation of the robust parameters/metrics (section 5.2), and the evaluation of the new offspring (line 9). This new offspring is added to the offspring population (line 10). When the offspring population is filled, the resulting union set between parents and offspring (line 12) is submitted to the fast non-dominated sort approach and crowding-distance computation (line 13). From this union set, the best ones are selected to update the parent population (line 14). Then, a new generation begins. At the end of all generations, the individuals in the first Front are the approximated Pareto optimal solutions (line 16). From this Pareto Front, one solution is chosen based on the $RM_{R\%}$.

The robustness criteria R_I included into the Robust-DM problem guides the EA to search in the robust regions of the search space. Finally, the decision making at the end

Algorithm 7 Pseudocode of the Robust-DM method based on NSGA-II

```

1: Find previous tap  $t_d^{h-1}$ 
2: Initialize parent population  $P$ 
3: Compute robust parameters/metrics. Evaluate  $P$ .  $g = 0$ 
4: while  $g \leq g_{max}$  do
5:   fast-non-dominated-sort( $P$ ). crowding-distance-assignment( $P$ )
6:   for  $i = 1$  to  $\text{size}(P)$  do
7:     Select two parents
8:     Crossover and multi-mutation operators under repair
9:     Compute robust parameters/metrics. Evaluate new offspring
10:    Add to offspring population  $Q$ 
11:  end for
12:  Combine  $R = P \cup Q$ 
13:  fast-non-dominated-sort( $R$ ). crowding-distance-assignment( $R$ )
14:  Select the best of  $R$  to update  $P$ .  $g = g + 1$ 
15: end while
16: Make a decision based on  $RM_{R\%}$  to choose one solution in the first Front.

```

of the evolution selects one solution $\vec{x}_{chosen}$ as follows:

$$\vec{x}_{chosen} = \text{argmin}[RM_{R\%}(\vec{x}_i) - RM_{R\%}^{spec} \mid RM_{R\%}(\vec{x}_i) \geq RM_{R\%}^{spec}] \quad (6.9)$$

where $\vec{x}_i$ is Pareto-optimal solution, $RM_{R\%}(\vec{x}_i)$ is the reliable robustness margin of $\vec{x}_i$, and $RM_{R\%}^{spec}$ is the specified level of robustness.

The reliable robust margin $RM_{R\%}$ is a metric that helps the distribution system operator to choose one among several trade-off solutions. So, specifying the level of robustness in terms of $RM_{R\%}$ means to select a solution that supports at least $RM_{R\%}^{spec}$ of load variations from the expected load demand. During one day of operation, it is possible to set different values of $RM_{R\%}^{spec}$. Thus, the hourly $RM_{R\%}^{spec}$ provides a baseline specification which can be used to prioritize greater values of $RM_{R\%}^{spec}$ in the hours of highly stochastic presence of uncertainty sources and smaller values of $RM_{R\%}^{spec}$ in the remaining hours.

6.4 Results and Discussion

This section presents the results of the case study. Several analyses are made in terms of robustness and costs. The ultimate objective of this chapter is undoubtedly to find solutions that are robust against uncertainties and, at the same time, economic in terms of operating costs. Such solutions are addressed as robust-economic solutions.

6.4.1 Configuration and input data

6.4.1.1 Base system, encoding/mapping, and decision variables

The distribution system used in the simulations is the IEEE 123 node test feeder (KERSTING, 2001b). No modification was made in the original system to preserve benchmark features. The one-line diagram of the IEEE 123 node test feeder can be seen in Appendix A.1.

The encoding, mapping models, and the decision variables are similar to those used in Chapter 5 (subsection 5.5.1.1), except that, instead of minimizing the active power intake into the system, now we are interested in minimizing the operating costs.

6.4.1.2 Parameters of the algorithms

Table 19 describes the common parameters used in the implementation of the Optimal-OC, Worst-case-OC, and Robust-DM methods. Conv-VR shares the same robustness index parameters.

Table 19: Parameters of robustness index and repair process

EAs	Parameters and values		
Robustness index	$step_i$: 0.1	c_{max} : 8	p_{max} : 0.000390625
Repair process	α : 0.001	β : 1.0	rc_{max} : 1,000

The EAs parameters are shown in Table 20. They were empirically found according to the historical practices in the literature that reports high and low probability for crossover and mutation, respectively. Optimal-OC and Worst-case-OC are based on GA, whereas Robust-DM, in NSGA-II.

Table 20: EAs parameters

Parameters	Optimal-OC	Worst-case-OC	Robust-DM
Population	40	40	20
Generation	100	400	200
Selection	$p = 2$	$p = 2$	$p = 2$
Elitism	$k = 10$	$k = 10$	-
Crossover	90%	90%	90%
Mutation	33%	33%	33%
N_{samp}	-	20	-

6.4.1.3 Input conditions for VVO

Similar to [Chapter 5](#), the system must accommodate the connection of a distributed generator at bus 76, which is the best location for loss minimization according to [Anwar and Pota \(2011\)](#). A photovoltaic generation capacity of 1 MVA is considered with unity power factor. The capacity factor of the PV generation was selected from persistent clear sky condition of a typical day in Brazilian Northeast region ([INPE, 2016](#)). The PV generation curve is presented throughout the results section and further detailed in [Appendix A.2](#).

This study uses a daily load curve characterized by heavy demand condition (see [Appendix A.2](#)), which was selected from an annual feeder load curve by taking the day with maximum load demand. These power measurement data are available on the OpenDSS package ([EPRI, 2020](#)).

The hourly energy costs were taken from [Sabillon-Antunez et al. \(2017\)](#) and the costs of tap changes from [Li et al. \(2017\)](#). The cost of switching SVRs is equal to 1.40 \$/tap-change and the cost of switching SC is equal to 0.24 \$/tap-change. These switching costs, which correspond to the depreciation cost for each switching operation, can be obtained based on both the cost of equipment installation and the number of switching that is allowable per day, since each tap-changing operation affects the equipment lifetime ([MALAKAR; GOSWAMI, 2013](#)). All these specified input conditions for VVO (PV generation, load demand and costs) are further detailed in the [Appendix A.2](#).

6.4.2 VVO design results

6.4.2.1 Robust margins

The following nomenclatures are present in the graphics which describe the robust margins:

- a) **upper/lower robust limit (RL_u or RL_l)**: is the maximum/minimum load that the control can handle without voltage issues;
- b) **robustness area (RA)**: is the area between the upper and lower limits. It comprises all scenarios that the control is able to operate without voltage issues;
- c) **robust limit of PV (pv_{RL})**: is the minimum PV output that the control is able to handle with;
- d) **robustness area of PV (pv_{RA})**: is the area between the expected PV output and the robust limit of PV. It comprises all PV scenarios that the control is able to operate without voltage issues;
- e) **expected load (k_{ref}) and PV (pv_{ref})**: are the daily load profile and PV output. They are input to the VVO problem. Based on these expected curves, the coordination is elaborated, determining the schedule of the VVO devices.

Figure 34—Figure 36 show the results considering load scenario changes (while the PV generation keeps following its respective curve), whereas Figure 37—Figure 39 show the results considering PV scenario changes (while the loading keeps following the load curve). All of them display the robust margins.

Figure 34 refers to the Optimal-OC method, i.e., the optimization that considers only minimization of the OC . The upper limit of the permitted load is close to the reference load, $RL_u^h \approx k_{ref}^h$. Therefore, the margin for loading increase is tight, since this will cause voltage violation. Despite of the optimal cost savings (shown later in subsection 6.4.2.2), the control has not guaranteed robustness for unpredictable loading deviation from the reference (forecast).

Figure 34: Robust margins of the Optimal-OC solution

Figure 35 outlines the Worst-case-OC solution, i.e., the optimization that considers the minimization of the OC under worst case scenarios. The upper limit of the permitted load is increased in comparison with the Optimal-OC solution. This means that the Worst-case-OC solution is more robust, having the capability of supporting more load variations.

Figure 35: Robust margins of the Worst-case-OC solution

Figure 36 depicts the proposed Robust-DM solution, which is a user-preferred solution based on $RM_{R\%} = 15\%$, during the hours of PV generation, and $RM_{R\%} = 10\%$, in the remaining hours of the day. The upper limit of the permitted load is greater than the Optimal-OC and more regular than the Worst-case-OC solution. Since the robust parameters/metrics are integrated into the multi-objective optimization, it is possible to have a better control of the robust specification.

Worst-case-OC and Robust-DM solutions obtained enlarged robustness area when comparing with the Optimal-OC solution. The percentage of increase are 3.05% and 12.37%, respectively. Moreover, the average of their upper robust margins are 2.4 and 5.3 times greater than that of the Optimal-OC, respectively, supporting higher load increase.

Therefore, if we concentrate efforts only in minimizing the operating costs under CVR perspectives, this may result in non-robust solutions. Meanwhile, it is possible to make use of techniques to improve the robust margins, which determine an important framework to ensure quality of power supply under loading scenario changes. In summary, the robust methods (Worst-case-OC and Robust-DM) can face greater load variations than the optimal cost savings solution.

Figure 36: Robust margins of the Robust-DM solution

Now, the analysis is made to verify the control robustness in the face of uncertainties of the PV generation. Figure 37 shows the limited capability of the Optimal-OC method to face stochastic behavior of renewable-based DG. The robust limit is close to the PV output estimation, $pv_{RL}^h \approx pv_{ref}^h$, most of the time. This reveals that small variations on the PV output may be enough to cause power quality problems regarding voltage violations. Therefore, the small margin of operation makes impracticable the control when renewable-based DG is present in the system.

On the other hand, Figure 38 and Figure 39 show the enlarged robustness area obtained by the robust methods (Worst-case-OC and Robust-DM). Both methods provide a robust control to deal with a wide range of PV power fluctuations. In relation to the

Optimal-OC robustness area, the percentage of increase are 245.37% and 478.38%, for the Worst-case-OC and Robust-DM solutions, respectively. So, they have increased capability of supporting PV power output variability caused by passing clouds, which is becoming a major concern for grid operators (CHEN et al., 2020).

Therefore, when the optimization considers only OC savings, this may result in a non-robust control which has limited capability to face the stochastic behavior of PV generation. On the other hand, methods like the Worst-case-OC and Robust-DM can be employed to guarantee the reliable system operation under this kind of uncertainty.

Figure 37: PV robust margin of the Optimal-OC solution

Figure 38: PV robust margin of the Worst-case-OC solution

Figure 39: PV robust margin of the Robust-DM solution

6.4.2.2 Operating costs

Table 21 shows the detailed results of the daily operating costs. Conv-VR is taken as the reference costs. As can be seen, all the optimization methods (Optimal-OC, Worst-case-OC, and Robust-DM) achieved cost savings when comparing with the conventional voltage regulation. This result highlights the importance of modeling the CVR goals, including CVR costs, via optimization designs. The best economic solution achieved 6.73% of cost savings. Also, the results express the relevance of reducing the number of tap changes so that OC could be diminished. All the optimization methods reduced the C_{SO} , proving again that the costs associated with the tap-changing operation have a decisive impact on the economics.

Table 21: Daily operating costs (heavy demand)

Methods	C_{SO}		C_{PI}		OC	
	\$	$\Delta\%$	\$	$\Delta\%$	\$	$\Delta\%$
Conv-VR	47.60	0.00	3844.50	0.00	3892.10	0.00
Optimal-OC	12.24	-74.29	3617.75	-5.90	3629.99	-6.73
Worst-case-OC	14.96	-68.57	3637.58	-5.38	3652.54	-6.15
Robust-DM	10.36	-78.24	3673.49	-4.45	3683.85	-5.35

Table 22 shows the hourly operating costs results. The values of the Optimal-OC solution represent the near-minimal OC from which we can compute the relative percentage difference ($\Delta\%$) of the other methods.

The robust methods (Worst-case-OC and Robust-DM) have costs associated with the robustness improvement, since they required higher amount of OC than the Optimal-OC (see section 6.2). However, their robustness costs are small, corresponding to \$22.55 and \$53.86 in a day, respectively. Therefore, by giving up a small percentage of cost savings (0.62% and 1.48% in a day, respectively), it is possible to implement a robust operation.

When the first hour is disregarded (because of the initialization costs), the maximum hourly $\Delta\%$ values are 2.17% and 2.83%, respectively, showing that both Worst-case-OC and Robust-DM solutions are capable of working close to the near-minimal OC , and even so to increase robustness. In summary, the robustness improvement can be designed at the expense of decreasing just a small amount of cost savings.

It is important to clarify that the Optimal-OC searches for near-minimal OC , which may not always be the smallest hourly costs among the methods due to dependence on previous tap decision. But, when the daily horizon is considered, the near-minimal OC results are well defined.

Table 22: Hourly operating costs (heavy demand)

Hour	Optimal-OC	Worst-case-OC		Robust-DM	
	OC [\$]	OC [\$]	$\Delta\%$	OC [\$]	$\Delta\%$
1	81.21	82.64	1.75	83.41	2.70
2	64.01	64.11	0.16	64.46	0.70
3	59.90	60.27	0.61	60.36	0.77
4	62.78	63.42	1.02	63.51	1.18
5	62.92	63.02	0.15	63.12	0.32
6	82.43	82.21	-0.26	82.98	0.67
7	103.88	105.07	1.15	105.28	1.35
8	114.14	113.08	-0.93	115.67	1.34
9	122.47	123.17	0.57	124.52	1.67
10	125.38	126.15	0.62	127.75	1.89
11	127.28	128.60	1.04	130.17	2.27
12	126.47	129.22	2.17	129.98	2.77
13	132.99	134.59	1.21	136.16	2.38
14	139.06	139.33	0.20	141.73	1.92
15	144.32	146.25	1.33	148.40	2.83
16	169.12	171.45	1.38	173.27	2.45
17	215.06	218.11	1.42	219.42	2.03
18	305.20	305.57	0.12	309.97	1.56
19	303.70	304.60	0.29	305.38	0.55
20	291.68	292.74	0.36	294.76	1.06
21	272.54	273.60	0.39	275.67	1.15
22	223.41	224.71	0.58	225.98	1.15
23	173.59	174.13	0.31	175.01	0.82
24	126.45	126.51	0.05	126.90	0.36
Total	3629.99	3652.54	0.62	3683.85	1.48

6.4.2.3 Robust metrics

Figure 40 shows the hourly results of the reliable robust margin. This metric represents the maximum allowable percentage of load deviation from the forecast that still keeps feasibility (subsection 5.2.3). As the Robust-DM requires the $RM_{R\%}$ baseline specification, which is the hourly specification of the reliable robust margin (Equation 6.9), this baseline level of robustness can be used for comparison purposes. In the following results, the baseline specification considers $RM_{R\%}^{spec} = 15\%$ during the hours with PV

generation and $RM_{R\%}^{spec} = 10\%$ in the remaining hours.

Among the methods, the Optimal-OC solution is the one with the smallest percentages of $RM_{R\%}$. Therefore, it supports only small uncertainties realization during the system operation. But, when worst-case scenarios are considered into the optimization process, the $RM_{R\%}$ values clearly increase. This is the case for the Worst-case-OC solution, which is more robust than the Optimal-OC. Nonetheless, the variation of the $RM_{R\%}$ metric is very large throughout the day, presenting weak robustness in certain hours (e.g., hour-18) and also good robustness in others (e.g., hour-4). Both Optimal-OC and Worst-case-OC methods are not capable to ensure the $RM_{R\%}^{spec}$ baseline. While the Optimal-OC results are well below the $RM_{R\%}^{spec}$ baseline during the day, the results of the Worst-case-OC oscillate closer (from bellow) to this reference. In contrast, the proposed Robust-DM solution can ensure feasibility according to the $RM_{R\%}^{spec}$ baseline throughout the day. This solution is much more robust than the Optimal-OC and much more uniform than the Worst-case-OC.

In summary, the Robust-DM and Worst-case-OC solutions are superior than the Optimal-OC in terms of robustness. Moreover, Robust-DM is able to ensure a certain level of robustness better than the Worst-case-OC, performing a reliable Volt/VAr control even under uncontrollable variations of load characterized by the $RM_{R\%}^{spec}$ baseline deviations from the forecast.

Figure 40: Hourly reliable robust margin

Table 23 helps to confirm the results extracted from Figure 40. It summarizes the average and standard deviation values of the $RM_{R\%}$ in one day of operation. The Optimal-OC has the smallest average of $RM_{R\%}$. For this reason, it represents the non-robust solution. On the other hand, the Worst-case-OC presents better average of $RM_{R\%}$ than the Optimal-OC, and consequently better robustness, but its $RM_{R\%}$ values oscillate a lot, confirmed by the greater standard deviation. Additionally, both the Optimal-OC and Worst-case-OC solutions cannot ensure the $RM_{R\%}^{spec}$ baseline. They exhibit lower values than the $RM_{R\%}^{spec}$ baseline at hours without PV generation (0.62% and 3.74%, respectively) and at hours with PV generation (0.89% and 3.61%, respectively). In contrast, the proposed Robust-DM solution is able to maintain the values of $RM_{R\%}$ greater than the baseline specification at all hours (10.16% and 15.18% at hours without and with PV generation, respectively). Moreover, besides the promising average of $RM_{R\%}$, the Robust-DM presents low standard deviation values. Therefore, the Robust-DM solution is able to achieve the desired level of robustness, having the $RM_{R\%}$ values close (from above) to the baseline specification.

Table 23: Daily reliable robust margin (heavy demand)

Hours	Methods	$RM_{R\%}$ [%]			
		Average	Std	Min	Max
1–7, 19–24	Optimal-OC	2.28	1.59	0.62	5.89
	Worst-case-OC	8.99	4.64	3.74	16.67
	Robust-DM	12.74	1.97	10.16	16.81
8–18	Optimal-OC	2.59	1.45	0.89	5.03
	Worst-case-OC	7.83	2.41	3.61	11.80
	Robust-DM	17.65	2.48	15.18	24.06

Table 24 shows the results for the reliable robust margin of PV (Equation 5.12) during the hours of PV generation. Again, the Optimal-OC is a non-robust solution. During a day of operation, it can present voltage violation for small deviations of PV output from the forecast. For example, at hour 15, only 4.83% of PV output variation is enough to cause this problem. In general, the Optimal-OC presented a mix of small, medium, and huge values of $RM_{R\%}$.

Table 24 also shows the huge PV robust margin improvement of the robust methods (Worst-case-OC and Robust-DM). Whereas $pv_{R\%}$ ranges from 31.42% to 100.00% in the Worst-case-OC solution, it ranges from 77.64% to 100.00% in the Robust-DM solution. These results mean that, in addition to support the stochastic behavior of PV generation due to many small clouds, these solutions can further tolerate complete covering or uncovering of the PV array by a large cloud at certain hours. Therefore, the robust

methods (Worst-case-OC and Robust-DM) ensure quality of power supply for PV scenario changes, keeping the voltages within the allowed limits.

Table 24: Hourly reliable robust margin of PV $pv_{R\%}$ (heavy demand)

Hour	pv_{ref} [pu]	$pv_{R\%}$ [%]		
		Optimal-OC	Worst-case-OC	Robust-DM
8	0.134	29.73	100.00	100.00
9	0.475	41.78	100.00	100.00
10	0.756	25.42	54.98	100.00
11	0.918	15.32	64.51	100.00
12	0.987	8.55	31.42	100.00
13	1.000	22.58	44.92	91.02
14	0.970	5.07	52.75	77.64
15	0.874	4.83	57.48	85.01
16	0.675	17.36	50.58	100.00
17	0.366	9.61	71.51	100.00
18	0.044	100.00	100.00	100.00

6.4.2.4 Robust-economic solutions

Figure 41 summarizes the results found so far, considering both aspects, robustness and costs, in a day operation. Now, the robust metric of the Conv-VR is also introduced in the analysis for a complete overview of all the methods (see tap solutions in Appendix C).

The Optimal-OC is the non-robust solution which was taken as the reference for cost savings, since it can achieve near-minimal OC . This solution, by the definition in Equation 6.1, has no costs associated with the robustness. So, when the VVO-based CVR is designed like the Optimal-OC, the result is a very sensitive solution under uncertainties of load/DG.

On the other extreme, the Conv-VR, which is not a VVO-based CVR, is the most robust solution due to its local automatic controls (subsection 2.2.1). But, at the same time, it is the most expensive in terms of OC . The Conv-VR is inefficient to perform the robust control, increasing the OC in 7.22% when comparing with the Optimal-OC. Also, the robustness costs of the Conv-VR is considerable (\$262.11), characterizing a robust but non-economic solution.

The Worst-case-OC has an oscillating robustness throughout the day due to the random scenarios which are created during the optimization process. Although this solution is more robust than the Optimal-OC, the Worst-case-OC's guaranteed robustness level is low at certain hours. Nevertheless, the robustness costs of the Worst-case-OC is very

small (\$22.56). It requires only 0.62% of operating costs increase in comparison with the Optimal-OC, characterizing a robust-economic solution. Indeed this result is a benchmark robustness costs because the method specifically searches for cost savings under worst case scenarios.

Similarly to the Worst-case-OC, the proposed Robust-DM is capable to greatly improve the robustness by sacrificing only a small amount of cost savings (i.e., only 1.48% of operating costs increase in comparison with the Optimal-OC). This result is very desirable, characterizing a robust-economic solution. The economic performance of the Robust-DM is very close to the benchmark robustness costs produced by the Worst-case-OC solution. Furthermore, the Robust-DM guarantees the $RM_{R\%}$ baseline specification with small amount of robustness costs (\$53.87). In general, the robustness of the Robust-DM is well-behaved according to the desired level of robustness defined by the baseline specification.

In conclusion, the VVO-based CVR design is able to produce efficient and cost savings solutions. But, uncertainties of load/DG must be properly dealt with. This thesis proposed the modeling of robust parameters/metrics to be incorporated into the optimization process to generate robust Volt/VAr solutions able to face these uncertainties. The proposed Robust-DM proved that robustness can be increased in a controlled manner so that a good balance can be obtained together with the economic aspect.

Figure 41: Integrated comparison between solutions

6.4.3 Robustness analysis

Monte Carlo sampling can be applied in order to check how the solution behaves in the face of forecast deviation. So, through Monte Carlo simulations, random daily scenarios of load demand and PV power generation are generated based on a normal distribution, in which the mean values are the load demand and PV output expectations and their standard deviations (σ_D and σ_{PV} , respectively) are given by three different test groups:

- a) Group 1: $\sigma_D = 1\%$ and $\sigma_{PV} = 5\%$;
- b) Group 2: $\sigma_D = 2\%$ and $\sigma_{PV} = 10\%$;
- c) Group 3: $\sigma_D = 4\%$ and $\sigma_{PV} = 20\%$.

For each group, 500 daily prediction scenarios of hourly load demands and PV outputs are randomly generated under the normal distribution and then this number is reduced to 100 by employing the simultaneous backward reduction algorithm (HEITSCH; RÖMISCH, 2003; WANG et al., 2014).

6.4.3.1 Robustness aspect

The features for uncertainty study is taken from Chapter 5, they are:

- a) Σ_{vv} : the number of daily voltage violations. It is possible to verify the minimum (Min), average (Avg), and maximum (Max) values of Σ_{vv} among all scenarios;
- b) IDS_{rate} : the rate of infeasible daily scenarios. It expresses the percentage of scenarios with voltage violation issues.

Table 25 and Table 26 show the results of these features when the solutions are submitted to scenario changes according to the test groups.

Table 25 shows that the Optimal-OC is non-robust to the variation in load/DG variables. From small to large uncertainties, Optimal-OC solution violates the permitted voltage limits. As the uncertainties increase, the Σ_{vv} measures (Min, Avg and Max) clearly increase. As a result, almost all scenarios are infeasible, confirmed by Table 26.

Worst-case-OC, Conv-VR, and Robust-DM solutions are much more robust to scenario realizations of load/DG variables than the Optimal-OC. Table 25 demonstrated that these solutions have no voltage violation issues under small uncertainties (Group 1) and, consequently, no infeasible scenarios (Table 26).

These solutions also perform well in the face of moderate uncertainties (Group 2). Worst-case-OC solution has small number of voltage violations. For example, in Table 25, the maximum number of voltage violations is 4. Correspondingly, Table 26 confirms that the Worst-case-OC presents small number of infeasible scenarios (7% are infeasible). On the other hand, Conv-VR and Robust-DM solutions present no voltage violation ($\Sigma_{vv} = 0$

in Table 25) under moderate uncertainties (Group 2) and can keep the operation feasible in all scenarios ($IDS_{rate} = 0\%$ in Table 26).

Although the robust VVO methods (Worst-case-OC and Robust-DM) have not been designed to deal with the large uncertainties of Group 3, in this study they are challenged by such group. Worst-case-OC presents greater number of voltage violations than the Robust-DM. For example, in Table 25, the maximum numbers of voltage violations are 64 and 16, respectively. Correspondingly, Table 26 confirms that Worst-case-OC presents more infeasible scenarios than the Robust-DM (81% and 6% are infeasible, respectively). Therefore, Robust-DM can perform better than the Worst-case-OC under highly stochastic behavior of load/DG, being a promising solution. When Conv-VR is considered in the analysis, it is the best solution to deal with Group 3 according to Table 25 and Table 26.

Therefore, the proposed Robust-DM solution is very robust to the load/DG forecast deviations. Table 25 and Table 26 proved that only under heavy uncertainties (Group 3) this solution presents voltage violation. But of course, a new design of the Robust-DM can be made using a new $RM_{R\%}$ baseline specification that supports the heavy uncertainties of Group 3.

Table 25: Number of daily voltage violations

σ_D, σ_{PV}	Σ_{vv}	Optimal-OC	Worst-case-OC	Conv-VR	Robust-DM
1%, 5%	Min	0	0	0	0
	Avg	1.4	0.0	0.0	0.0
	Max	21	0	0	0
2%, 10%	Min	0	0	0	0
	Avg	17.2	0.2	0.0	0.0
	Max	59	4	0	0
4%, 20%	Min	11	0	0	0
	Avg	90.8	14.8	0.0	0.4
	Max	183	64	0	16

Table 26: Infeasible daily scenarios rate

σ_D, σ_{PV}	IDS_{rate}	Optimal-OC	Worst-case-OC	Conv-VR	Robust-DM
1%, 5%	[%]	50	0	0	0
2%, 10%	[%]	97	7	0	0
4%, 20%	[%]	100	81	0	6

Another way to visualize the feasibility of the solutions is by distributing the number of infeasible scenarios that can be observed in a certain amount of time. The

histogram in Figure 42, printed in 3 by 4 subplot matrices, shows the percentage of daily scenarios δ_τ in which the amount of time τ_{vv} is spent with voltage violations. For example, the Worst-case-OC presents $\delta_\tau = 30\%$ and $\tau_{vv} = 2$ under Group 3 of uncertainties. This means that 30% of scenarios have voltage violations during 2 hours of the daily operation. In fact, the Optimal-OC is the solution that spends more hours with voltage violations. Differently, the other solutions perform well in view of the diverse range of uncertainties (except Worst-case-OC under Group 3), spending few hours with voltage violations when these occur.

To sum up, a method that only seeks for costs saving, the case of the Optimal-OC solution, proves to be impractical in real-world CVR problems due to the stochastic behavior of load/DG which influences the feasibility of the system operation. But, it is possible to design a control much immune to these uncertainties, like the Worst-case-OC and Robust-DM solutions, and still maintain the optimal characteristics.

Figure 42: Feasibility of VVC designs against test groups

6.4.3.2 Economic aspect

Together with the robustness to deal with load/DG uncertainties, the economic aspect should be analyzed. On one hand, very robust solutions can damage the CVR goals and be expensive in terms of operating costs. On the other hand, very efficient CVR solutions can be impractical in real world conditions due to their lack of capacity to deal with the stochastic behavior of the load/DG variables. Therefore, a promising solution must represent a good balance between robustness and costs.

Figure 43–Figure 45 show the operating costs under load/DG uncertainties for the groups 1, 2, and 3, respectively. Of course, as the uncertainties increase, the variation of operating costs (the interval between minimum and maximum) also increases.

These figures confirm once again that the Worst-case-OC and Robust-DM solutions are capable of improving the robustness by sacrificing only a small amount of cost savings. The following average values are computed based on the results from all groups of uncertainties. The operating costs increase are 0.61% and 1.47% for the Worst-case-OC and Robust-DM solutions, respectively. In other words, the economic performance of the Robust-DM is close to the benchmark costs produced by the Worst-case-OC solution. Both Worst-case-OC and Robust-DM solutions are robust-economic solutions. Although Conv-VR is very robust, it is expensive in terms of operating costs. The robustness costs associated with the Conv-VR are 12.3 times and 5.1 times greater than those associated with the Worst-case-OC and the Robust-DM, respectively.

Therefore, the results of this section highlighted the behavior of all solutions under several ranges of load/DG uncertainties. A good balance between operating costs and robustness was achieved by the Worst-case-OC and Robust-DM solutions. At a small cost amount, they were able to increase robustness to face the stochastic behavior of the load/DG variables.

6.4.4 CVR analysis

In Table 27, the Conv-VR — which automatically changes the tap settings to correct voltage violation (no optimization in this case) — is considered as the base case of energy consumption. The term $\Delta\%$ means the percentage of energy reduction in relation to the base case.

The active power intake in the system has been used as a way to pursue energy savings by voltage reductions. Accordingly, Table 27 shows that all the VVO-based CVR methods (Optimal-OC, Worst-case-OC, and Robust-DM) are capable of reducing the daily energy consumption.

Although the Optimal-OC is the solution with greatest energy savings, the robust solutions (Worst-case-OC and Robust-DM) are also efficient to achieve this CVR goal.

Figure 43: Operating costs under load/DG uncertainties ($\sigma_D = 1\%$, $\sigma_{PV} = 5\%$) Figure 44: Operating costs under load/DG uncertainties ($\sigma_D = 2\%$, $\sigma_{PV} = 10\%$)

Figure 45: Operating costs under load/DG uncertainties ($\sigma_D = 4\%$, $\sigma_{PV} = 20\%$)

Naturally, the robust solutions require energy savings reduction to increase robustness. But, abdicating of a small amount of energy savings is enough to greatly improve the robustness.

Table 27 also shows the components of the total energy consumed by the substation, that is, the portions related to load consumption and electrical losses. It is important to note that energy saving is mainly accomplished due to reduction in load consumption. This highlights that the presence of voltage dependent loads is crucial for CVR deployment. Although there was an increase in losses due to constant power loads present in the system (see subsection 2.1.3.2), the final result proved that the CVR was effective in producing energy savings.

Table 27: Comparative daily energy savings [MWh]

	Conv-VR	Optimal-OC		Worst-case-OC		Robust-DM	
	MWh	MWh	$\Delta\%$	MWh	$\Delta\%$	MWh	$\Delta\%$
Load	57.596	54.083	-6.10	54.414	-5.52	54.877	-4.72
Losses	1.143	1.174	2.63	1.151	0.62	1.171	2.39
Total	58.739	55.257	-5.93	55.564	-5.40	56.048	-4.58

Finally, all VVO-based CVR methods fulfill the CVR effectiveness by reducing

voltages on the system. Table 28 shows the daily average voltage as a way of visualizing this reduction. Conv-VR method has higher levels of voltage then VVO-based CVR methods.

Table 28: Comparative daily average voltage [V]

Conv-VR		Optimal-OC		Worst-case-OC		Robust-DM	
V		V	$\Delta\%$	V	$\Delta\%$	V	$\Delta\%$
1.017		0.948	-6.79	0.951	-6.47	0.955	-6.05

Additionally, it is worth pointing out the peak-load relief provided by the CVR technique. Figure 46 shows the hourly energy consumption by the distribution system, confirming again that the VVO-based CVR methods are able to produce energy savings compared to conventional voltage regulation. The peak-load level occurs at hour 7 pm, where the active power peak is reduced from 3.517 MW, in the base case, to 3.375 MW, 3.388 MW, and 3.412 MW for Optimal-OC, Worst-case-OC, and Robust-DM, respectively. These values correspond to 4.03%, 3.67%, and 2.98% of MW peak-load alleviation in the distribution system, respectively. Therefore, peak-load relief is also accomplished by the VVO-based CVR methods.

Figure 46: Hourly energy consumption

6.4.5 Computational efforts

Finally, the last aspect of this case study is related to the computational efforts required by the robust VVO-based CVR methods. In the context of smart grid, fast methods are preferred for real-time applications. Table 29 details the computational time spent by the robust VVO-based CVR methods to compute the robust-economic solution per hour of system operation.

The Robust-DM method is much faster than the Worst-case-OC method to solve the optimization problem. Specifically, the Robust-DM is 12 times faster than the Worst-case-OC. The ability of Robust-DM to reduce the computational effort in solving the CVR problem based on VVO is remarkable.

Therefore, the Robust-DM is a promising method for finding robust-economic solutions close to the benchmark Worst-case-OC method, but with further ability to work in a real-time scale.

Table 29: Computational time per hour of system operation

	Worst-case-OC	Robust-DM
Min	690.57s	60.70s
Avg	790.79s	67.45s
Max	998.49s	74.73s

6.5 Concluding remarks

This chapter conducted a case study to investigate the costs associated with the robustness improvement of the VVO-based CVR. The robustness costs were estimated by the cost increase related to a robust solution in comparison with the optimal costs. This manner is straightforward, giving a consistent parameter for comparison among different methods.

When we concentrate efforts only in minimizing the operating costs (Optimal-OC method), the result is a non-robust solution, which is configured by small percentages of $RM_R\%$. The margin for load increase (or DG decrease) is tight, making the operation sensible to load/DG deviations from the forecast — voltage standards can be easily violated by these uncertainties. Nonetheless, this solution is useful as a reference for optimal costs, helping to estimate robustness costs of robust solutions.

Focusing on robust-economic solutions, Worst-case-OC and Robust-DM methods were employed to guarantee the reliable system operation under uncertainties. Their solutions obtained enlarged robustness area when comparing with the Optimal-OC, providing

a robust control to deal with a wide range of PV fluctuations and load variations, which was confirmed by the increased percentages of $RM_R\%$.

The daily robustness costs associated with the Worst-case-OC and Robust-DM solutions were \$22.56 and \$53.87, respectively, corresponding to 0.62% and 1.46% of their daily operating costs. Therefore, these solutions required small amount of costs to obtain enhanced robustness. Correspondingly, to implement a robust operation, they required to abdicate of a small percentage of cost savings (0.62% and 1.48%, respectively). Therefore, from the trade-off point of view, the robustness improvement could be designed at the expense of sacrificing just a small amount of cost savings. Differently, the Conv-VR proved to be robust, but not economical, since its robustness costs reached much higher values (up to 12 times) than those obtained by the robust VVO methods.

Monte Carlo simulations were applied to check how these solutions behave in the face of several ranges of load/DG uncertainties. A good balance between operating costs and robustness was achieved by the Worst-case-OC and Robust-DM solutions. Moreover, through CVR analysis, all the VVO-based CVR methods (Optimal-OC, Worst-case-OC, and Robust-DM) were effective in performing the CVR, i.e., they were able to produce energy savings by voltage reductions. Even in search of robust solutions, the Worst-case-OC and Robust-DM methods preserved the CVR features.

In conclusion, both Worst-case-OC and Robust-DM solutions were efficient to implement the robust-economic Volt/VAr control. They were capable to work close to the near-minimal operating costs, and even so to increase robustness. Notably, the proposed Robust-DM was able to find a robust-economic solution close to the benchmark Worst-case-OC method, but with further two superior features: 1) the level of robustness could be ensured in a controlled manner, and 2) the computational effort could be greatly reduced. Therefore, the proposed Robust-DM is a promising method for smart grid applications due to its advanced capability of finding robust-economic CVR solutions in a real-time scale.

7 CONCLUSIONS AND FUTURE WORKS

This chapter presents the conclusive remarks regarding the PhD research and also suggestions for further improvement of the Volt/VAr control in modern distribution systems.

7.1 Conclusions

The operation of distribution systems is evolving toward more optimization, real-time application, and intelligent algorithms (DUGAN; MCDERMOTT, 2011). With this in mind, Volt/VAr control has much potential to become more advanced via smart grid capabilities (MANBACHI et al., 2017). For this reason, the proposed methods in this thesis followed these research threads, trying to fulfill the gap between conventional and advanced VVO solutions (MANBACHI et al., 2014).

This thesis focused in energy efficiency by considering the CVR, which is a cost-effective way of saving energy. Besides, the effects on the CVR goals by the number of tap-changing operations of voltage regulating devices were investigated to attain real-world conditions. Thus, the starting point of the research was to solve this Volt/VAr multi-objective optimization problem, which was a challenging task for EAs in terms of meeting voltage limit constraints and reaching near optimal solutions due to the time coupling combinatorial complexity. These results motivated the development of a new specialized evolutionary system for Volt/VAr optimization to efficiently solve the multi-objective problem.

The first step was restricting the search space. The proposed heuristic permitted to remove impractical tap settings. Then, the simulations demonstrated that the daily voltage violations persist for benchmark approaches (typical genetic operators of NSGA-II and MOPSO-based methods). This problem was properly solved by the proposed repair process, which enabled these benchmark methods to generate feasible solutions. However, due to individuals trapped into a local optimum, these methods showed excessive switching of the Volt/VAr equipment and sub-optimal active power intake values. For this reason, the specialized mechanisms of search, HTP and TAI, was proposed in the SES-VVO to improve the performance objectives. The HTP operator yielded substantial tap operations reduction and the TAI operator pressured even more the search for near-optimal active power intake values. Then, the last proposed procedure produced a larger amount of multiple diversified near-optimal solutions and achieved a covered Pareto gain.

The superiority of the proposed SES-VVO was verified in all performance indices when comparing with benchmark approaches (typical genetic operators of NSGA-II and

MOPSO-based methods). This result highlights the importance of developing specialized mechanisms of search to empower EAs to solve efficiently the VVMO problem.

The potentialities of the proposed SES-VVO could be explored through day-ahead operation planning and hourly decision-making approaches. The first strategy pursues multiple candidate solutions, whereas the second one, a user-preferred solution based on costs. Specifically, the DM-SES-VVO is an advanced speed-up approach that has potential for real-time operation. It achieved superior performance in a real-time scale and was capable of dealing with the variation of load demand and the intermittence of PV generation. In return, DM-SES-VVO requires deployed smart grid technologies (e.g., AMI and DMS) to implement and operate.

It was proposed to include the switching costs into the operating costs estimation so that the tap-changing operations could reflect the switching risk assessment of the distribution system operator (like the depreciation cost for each switching operation). As a result, it was demonstrated that the switching costs have a decisive impact on the economics when the CVR goals are pursued by the VVO. If tap-changing actions are not carefully considered, the operating costs can increase significantly. For this analysis, the costs per tap-changing action were taken from the literature. In general, modeling CVR as VVO problems is an effective way to produce cost savings when efficient methods are employed (results achieved up to 11% of cost savings in comparison with the conventional voltage regulation).

The advanced robustness strategy of the DM-SES-VVO relies on both the optimization horizon constituted by the threefold input (previous control, actual data, and forecasts) and the decision-making ability. This scheme enables the DM-SES-VVO to deal with scenario changes. On the other hand, although the SES-VVO can be applied to solve the series of equivalent deterministic scenarios that compose the stochastic optimization framework, post-optimization sensitive analysis of the operation planning (OP-SES-VVO) led to infeasible solutions when facing load/DG stochasticity. When the CVR goals are being rigorously pursued by VVO, scenarios different from that used in the optimization may deteriorate the coordinated control, resulting in voltage issues. This unexpected result motivated the research to further investigate robustness in VVO-based CVR.

This thesis has revealed that VVO-based CVR solutions lie on the boundary of the feasible domain. Any increase in loading (or diminishing in DG) can cause voltage violations. As the scale of changes increases, the problem becomes bigger (more number of nodes and amount of time with such issues). But, real-world CVR problems demand solutions that perform well against uncertainties during the system operation. As the integration of renewable-based DGs (and other DERs) is evermore increasing, their stochastic behavior can lead to poor voltage quality due to the non-robust VVO designs.

To ensure voltage standards, even for scenario changes, a robustness framework, con-

stituted by parameters and metrics, was proposed to evaluate how robust is a VVO design when facing load/DG uncertainties. The greatest advantages of these parameters/metrics are that they do not require a presumed probability distribution of the uncontrollable variables or parameters related to probability models; nor do they need evaluating large numbers of scenarios to approximate the performance of the solution against a variety of uncertainty realizations.

In one hand, the proposed robustness framework can be used to both investigate the ability of the scheduled control to support scenario changes and compare different VVO designs under the robustness perspective. On the other hand, the robustness framework can be incorporated into the optimization problem to produce robust solutions according to a desired level of robustness. Thus, the proposed parameters/metrics can be used not only for robustness analysis, but also for designing robust solutions.

The robust VVO-based CVR (named Robust-CVR) was designed as a multi-objective optimization problem so that the CVR goals could be pursued without neglecting the robustness of the system operation. The results demonstrated a clearly advantageous balance between performance and robustness, that is, by abdicating of a small amount of energy savings it is possible to reach huge gains in robustness. In other words, the Robust-CVR method enhances the robustness of the system operation, upholding power quality for scenario changes and preserving near-optimal CVR goals. In summary, the Robust-CVR could ensure a robust control together with better energy savings than conventional voltage regulation methods.

The Robust-CVR solution was capable to face diverse realizations of the uncertainties, encouraging a further investigation about the costs associated with the robustness improvement of the VVO-based CVR. So, it was proposed to estimate these costs by the cost increase related to a robust solution when comparing with the optimal costs.

Just as when performance was the goal of VVO-based CVR, focusing efforts only on minimizing operating costs resulted in non-robust solutions. In other words, the power quality regarding voltage standards can be easily damage by load/DG uncertainties during system operation. So, the Robust-DM method was designed as a multi-objective optimization problem so that trade-offs between operating costs and robustness could be searched. In addition, decision-making was applied according to the level of robustness specified per hour (baseline specification). Thus, the hours of greater uncertainties could be prioritized with a higher level of robustness.

The results of the Robust-DM method demonstrated that robust solutions can be designed at the expense of a small amount of costs. Numerically, the percentage of operating costs related to robustness was 1.46%. This value corresponds to the average level of robustness given by $RM_{R\%}$ equals to 14.99%, which guaranteed a reliable system operation under a wide range of load/PV forecast deviations — the Robust-DM solution

was very robust to small ($\sigma_D = 1\%$ and $\sigma_{PV} = 5\%$) and moderate ($\sigma_D = 2\%$ and $\sigma_{PV} = 10\%$) uncertainties, presenting voltage violations only under heavy uncertainties ($\sigma_D = 4\%$ and $\sigma_{PV} = 20\%$) in 6% of the scenarios. But of course, a new design of the Robust-DM can be made using a new $RM_{R\%}$ baseline specification that supports the heavy uncertainties. In addition, from trade-off point of view, we can say that the robustness improvement can be designed at the expense of sacrificing just a small amount of cost savings (numerically, it was 1.48%). In sum, the Robust-DM solution was capable to work close to the near-minimal operating costs, and even so to increase robustness.

Comparisons with other methods were carried out to validate the Robust-DM method. Indeed, this proposed method was able to find a robust-economic solution close to a benchmark robust optimization method, but with further two superior features: 1) the level of robustness could be ensured in a controlled manner, and 2) the computational effort could be greatly reduced. Therefore, the proposed Robust-DM is a promising method for smart grid applications due to its advanced capability of finding robust and cost-effective CVR solutions on a real-time scale.

The proposed methods have obtained good solutions (not necessary the best) in a reasonable and practical time, as in most applications that must balance the computing resources and solution quality (YANG; KOZIEL, 2011). When the engineering design is based on computer simulation models, the evaluations of the objective functions are often time-consuming. Nevertheless, the OpenDSS has shown reduced cost of power flow evaluations, being able to interface external platform programming so that a complete intelligent system could be developed. Besides, the optimization engine based on EAs have permitted to model the VVMO problem as a black-box type of optimization. Thus, objective functions and constraints did not need to be expressed in explicit analytical form.

In conclusion, the new intelligent systems, proposed in this thesis, could provide efficient EAs for robust Volt/VAr control in modern power distribution systems. The general goal was to face the recent operating scenario challenges and to make use of the technological advances in infrastructure. Indeed, these intelligent systems can be part of an advanced centralized framework — like the IVVC which provides all necessary infrastructure — to implement the proposals of this thesis in real-life power distribution systems aiming at achieving efficient, robust and reliable Volt/VAr control solutions.

7.2 Future works

The opportunities for improvement and advancement of Volt/VAr control designs still remain. Interesting suggestions for future research, based on the results of this thesis, are as follows:

- implement the proposals of this thesis in real-time power system simulator;
- explore the generalization of the SES-VVO mechanisms of search in different EAs;
- investigate the effects of other DERs (e.g. ESD and EV) on the robustness of the system operation;
- consider the smart inverters' capability of injecting reactive power as a way to improve robustness;
- apply other techniques, such as parallel computing or machine learning, to further speed up the SES-VVO in large scale optimization problems.

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Appendix

APPENDIX A – TEST SYSTEMS AND PARAMETER SETTINGS

A.1 IEEE test feeders

Figure 47: The one-line diagram of the IEEE 34 node test feeder

Figure 48: The one-line diagram of the IEEE 123 node test feeder

A.2 Specified input conditions for VVO

Costs of switching

The switching costs used in [Chapter 4](#) were taken from [Manbachi et al. \(2016a\)](#), whose values are: 0.05γ (\$/tap-change) for OLTC, 0.05β (\$/tap-change) for SVRs, and 0.05δ (\$/kvar-year) for SCs, where $\gamma = \beta = \delta = 100$. Whereas, in [Chapter 6](#), the switching costs were taken from [Li et al. \(2017\)](#), whose values are: 1.40 (\$/tap-change) for SVRs and 0.24 (\$/tap-change) for SC.

Energy cost

The hourly energy cost was taken from ([SABILLON-ANTUNEZ et al., 2017](#)). They are detailed in [Table 30](#).

Table 30: Energy cost

Hour (h)	Energy cost (\$/kWh)	Hour (h)	Energy cost (\$/kWh)	Hour (h)	Energy cost (\$/kWh)
1	0.0385	9	0.0529	17	0.0933
2	0.0327	10	0.0606	18	0.0962
3	0.0317	11	0.0673	19	0.0895
4	0.0336	12	0.0721	20	0.0875
5	0.0327	13	0.0798	21	0.0837
6	0.0394	14	0.0847	22	0.0721
7	0.0423	15	0.0866	23	0.0625
8	0.0442	16	0.0914	24	0.0529

PV generation

The hourly PV generation was taken from (INPE, 2016). They are detailed in Table 31.

Table 31: PV generation

Hour (h)	PV output (pu)	Hour (h)	PV output (pu)	Hour (h)	PV output (pu)
1	0	9	0.475	17	0.366
2	0	10	0.756	18	0.044
3	0	11	0.918	19	0
4	0	12	0.987	20	0
5	0	13	1.000	21	0
6	0	14	0.970	22	0
7	0	15	0.874	23	0
8	0.134	16	0.675	24	0

Load demand

The hourly load demand of Chapter 4 and Chapter 5 was taken from Jardini et al. (2000), whereas the load demand of Chapter 6 was taken from the OpenDSS package (EPRI, 2020). The value of these curves are detailed in Table 32–Table 34.

Table 32: Load demand of Chapter 4

Hour (h)	Load demand (pu)	Hour (h)	Load demand (pu)	Hour (h)	Load demand (pu)
1	0.332	9	0.855	17	0.841
2	0.302	10	0.900	18	0.835
3	0.322	11	0.839	19	0.768
4	0.301	12	0.813	20	0.759
5	0.315	13	0.829	21	0.760
6	0.422	14	0.865	22	0.753
7	0.667	15	0.853	23	0.495
8	0.825	16	0.851	24	0.359

Table 33: Load demand of [Chapter 5](#)

Hour (h)	Load demand (pu)	Hour (h)	Load demand (pu)	Hour (h)	Load demand (pu)
1	0.274	9	0.818	17	0.910
2	0.287	10	0.845	18	0.796
3	0.307	11	0.869	19	0.650
4	0.290	12	0.916	20	0.606
5	0.291	13	0.512	21	0.598
6	0.297	14	0.887	22	0.442
7	0.250	15	0.943	23	0.336
8	0.390	16	0.950	24	0.299

Table 34: Load demand of [Chapter 6](#)

Hour (h)	Load demand (pu)	Hour (h)	Load demand (pu)	Hour (h)	Load demand (pu)
1	0.627	9	0.825	17	0.793
2	0.580	10	0.837	18	0.930
3	0.562	11	0.834	19	0.977
4	0.558	12	0.815	20	0.965
5	0.570	13	0.792	21	0.944
6	0.620	14	0.776	22	0.899
7	0.716	15	0.760	23	0.808
8	0.791	16	0.753	24	0.701

APPENDIX B – CONVENTIONAL VOLTAGE REGULATION

The conventional voltage regulation (Conv-VR) automatically changes the tap settings of the OLTC and SVRs to accomplish the automatic control by LDC as shortly described in [subsubsection 2.2.1.2](#), whereas the reactive power of the capacitors are considered fixed. Therefore, there is no optimization in this case.

The parameters for the OLTC and SVRs are: V_{set} is the set voltage, N_{PT} and N_{CT} are the ratios for the potential and current transformers, BW is the bandwidth in volts, $R' + jX'$ is the compensator impedance in volts, and delay refers to the time delay setting in seconds. [Table 35](#) and [Table 36](#) present all these settings.

Table 35: Parameter settings of the Conv-VR for the IEEE 34 bus node test feeder

Equipment		Parameter settings						
OLTC		tap: 1.05						
SC.1 (3-phase)		300 kvar						
SC.2 (3-phase)		450 kvar						
SVR.1	V_{set} :	N_{PT} :	N_{CT} :	BW:	R' :	X' :	delay:	
	122 V	120	100	2 V	2.7 V	1.6 V	15 s	
SVR.2	V_{set} :	N_{PT} :	N_{CT} :	BW:	R' :	X' :	delay:	
	124 V	120	100	2 V	2.5 V	1.5 V	30 s	

Table 36: Parameter settings of the Conv-VR for the IEEE 123 bus node test feeder

Equipment		Parameter settings					
SC (3-phase)		600 kvar (bus 83)					
SCs (1-phase)		50 kvar (buses 88a, 90b, and 92c)					
SVR.1 (3-phase)	V_{set} : 120 V	N_{PT} : 20	N_{CT} : 700	BW: 2 V	R' : 3.0 V	X' : 7.5 V	delay: 15 s
SVR.2 (1-phase: a)	V_{set} : 120 V	N_{PT} : 20	N_{CT} : 50	BW: 2 V	R' : 0.4 V	X' : 0.4 V	delay: 15 s
SVR.3 (1-phase: a)	V_{set} : 120 V	N_{PT} : 20	N_{CT} : 50	BW: 1 V	R' : 0.4 V	X' : 0.4 V	delay: 15 s
SVR.3 (1-phase: c)	V_{set} : 120 V	N_{PT} : 20	N_{CT} : 50	BW: 1 V	R' : 0.4 V	X' : 0.4 V	delay: 15 s
SVR.4 (1-phase: a)	V_{set} : 124 V	N_{PT} : 20	N_{CT} : 300	BW: 2 V	R' : 0.6 V	X' : 1.3 V	delay: 15 s
SVR.4 (1-phase: b)	V_{set} : 124 V	N_{PT} : 20	N_{CT} : 300	BW: 2 V	R' : 1.4 V	X' : 2.6 V	delay: 15 s
SVR.4 (1-phase: c)	V_{set} : 124 V	N_{PT} : 20	N_{CT} : 300	BW: 2 V	R' : 0.2 V	X' : 1.4 V	delay: 15 s

APPENDIX C – DAILY TAP SOLUTIONS

Tap solutions of the methods of Chapter 6 are presented in Figure 49–Figure 56.

Figure 49: Daily tap solutions of SVR.1 (three-phase)

Figure 50: Daily tap solutions of SVR.2 at phase A

Figure 51: Daily tap solutions of SVR.3 at phase A

Figure 52: Daily tap solutions of SVR.3 at phase C

Figure 53: Daily tap solutions of SVR.4 at phase A

Figure 54: Daily tap solutions of SVR.4 at phase B

Figure 55: Daily tap solutions of SVR.4 at phase C

Figure 56: Daily number of capacitor banks in service of SC.1 (three-phase)