



Application of Optimization in Regional Distribution Network Reconfiguration

Nour Karnib

► To cite this version:

Nour Karnib. Application of Optimization in Regional Distribution Network Reconfiguration. Other [cs.OH]. ISAE-ENSMA Ecole Nationale Supérieure de Mécanique et d'Aérotechnique - Poitiers, 2025. English. ⟨NNT : 2025ESMA0001⟩. ⟨tel-04977979⟩

HAL Id: tel-04977979

<https://theses.hal.science/tel-04977979v1>

Submitted on 5 Mar 2025

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



HAL Authorization

THESIS

Submitted for the degree of
**DOCTOR OF PHILOSOPHY FROM ECOLE NATIONALE
SUPERIEURE DE MECANIQUE ET D'AEROTECHNIQUE**

(National Degree - Decree of May 25, 2016 Modified by Decree of August 26, 2022)

Doctoral School :
MIMME Mathématiques, Informatique, Matériaux, Mécanique, Énergétique

Field of Research : Computer Science and Applications

Defended by :
Nour Karnib

**Application of Optimization in Regional Distribution
Network Reconfiguration**

Thesis supervisor : **Emmanuel Grolleau**
Co-supervisor : **Antoine Bertout**

EXAMINATION BOARD

Reviewers:

Marc SEVAUX, Professor, Université Bretagne Sud
Ameur SOUKHAL, Professor, Université de Tours

Examinors:

Nadia BRAUNER, Professor, Université Grenoble Alpes

Supervisors:

Antoine BERTOUT, Associate Professor, Université de Poitiers
Emmanuel GROLLEAU, Professor, ISAE-ENSMA



RÉGION
**Nouvelle-
Aquitaine**



Acknowledgments

I would first like to express my sincere gratitude to the members of my thesis jury. I extend my heartfelt thanks to Marc SEVAUX and Ameer SOUKHAL for their time and effort in reviewing my thesis. I am also deeply grateful to Nadia BRAUNER for accepting to be a member of my jury.

A special thank you to my supervisor, Emmanuel GROLLEAU, for his invaluable guidance, open-mindedness, and continuous support throughout these three years. His dedication and efforts greatly contributed to the smooth progress of this thesis. I am also very grateful to my co-supervisor, Antoine BERTOUT, for his insightful advice and unwavering presence.

I extend my appreciation to all the members of LIAS, the staff at ENSMA and the members of SRD for their support. Lastly, I would like to thank my family—especially my mother—for her constant presence, as well as my friends and loved ones, who have been by my side throughout this journey.

Contents

1	Distribution Networks and Distribution System Operators: Structure and Exploitation	3
1.1	Electrical power system of France	4
1.2	Introduction to distribution networks	5
1.3	Electrical engineering	6
1.4	Components of the Distribution Network	10
1.5	Structure and exploitation	14
1.6	Load flow	18
1.7	Optimization	22
1.8	Conclusion	24
2	Context and Thematic: Labcom Alienor	25
3	The Distribution Network Reconfiguration problem	33
3.1	The distribution network reconfiguration problem (DNR problem)	34
3.2	Resolution approach	35
3.3	State of the art	38
3.4	Model description	42
3.5	A MIQP with bidirectional binary variables	44
3.6	A MIQP with one binary variable per edge	54
3.7	Challenges and contributions	59
4	A network reduction method for the Distribution Network Reconfiguration problem	61
4.1	Introduction	62
4.2	Contribution: A network reduction method for the DNR problem	63
4.3	Experiments	66
4.4	Conclusion	68
5	Low-Impact Switch Elimination Method for Distribution Network Reconfiguration for Large-Scale Networks	69
5.1	Literature review	70
5.2	Low-impact switch elimination method	70
5.3	Experiments	72
5.4	Conclusion	75
6	Load Curve-Based Optimization	77

6.1	Introduction	78
6.2	Mathematical Model	81
6.3	Accounting for the switching cost	87
6.4	Experiments	89
6.5	Single Reconfiguration versus Fixed Reconfiguration	91
6.6	Conclusion	97
7	Distributed Generations Curtailment for Maintaining Voltage Stabi-	
	lization	99
7.1	Introduction	100
7.2	Relaxation of the voltage constraints	101
7.3	Power Curtailment model	102
7.4	Experiments	103
7.5	Conclusion	107
8	Conclusions and Perspectives	109
9	Résumé Etendu en Français	111
9.1	Introduction	111
9.2	Contexte et thématique : Labcom ALIENOR	113
9.3	Réseaux de Distribution et Gestionnaires de Réseau de Distribution	114
9.4	Approches de résolution du problème DNR : Méthodes Exactes	118
9.5	Une Méthode de Réduction de réseaux pour le Problème de Reconfiguration des Réseaux (DNR)	121
9.6	Méthode d'élimination des interrupteurs à faible impact pour le problème de reconfiguration des réseaux de distribution à grande échelle	125
9.7	Optimisation basée sur les courbes de charge	129
9.8	Réduction ponctuelle de la production décentralisée pour maintenir la sta- bilité de la tension	133
9.9	Conclusions et perspectives	136
	Bibliography	139

List of Figures

1.1	The french electrical network	5
1.2	The admittance model of a line $(1, 2)$	12
1.3	A radial graph	15
1.4	A meshed graph	15
1.5	Kirchhoff current at k	18
1.6	Newton-Raphson method on a single variable function	21
1.7	An example of a convex hull.	24
1.8	An example of a non-convex hull: there exists a segments joining y and z that lies outside the hull	24
3.1	An underlying graph	34
3.2	A feasible configuration	34
3.3	A decision tree	35
3.4	A decision tree	36
3.5	A line as a pi-model	43
3.6	An edge (u, v) splitted into two binary variables	45
3.7	A vertex v must be conducted by one and only vertex	45
3.8	The underlying graph	46
3.9	A feasible solution	46
3.10	The approximation of $yp(u, v)^2 + yq(u, v)^2 = S_{max}(u, v)^2$ for an edge (u, v) . .	52
4.1	$\{1,2,3,4\}$ are merged into w_0 and $\{5,6,7\}$ into the source	63
4.2	Flowchart of network reduction	65
5.1	Percentage for switches of being ON (closed).	73
5.2	Scatter plot of the initial OPs + OP1 + OP2.	73
6.1	Optimization on load and generation curves	79
6.2	Active power losses at each hour for fixed and free mutiple reconfiguration . .	91
6.3	Results for each switch (u, v) for OP_1	92
6.4	Results for each switch (u, v) for OP_2	92
6.5	The set of operating points $(load, prod)$	93
6.6	Solution of the switches in the Fixed Reconfiguration case	94
6.7	Comparison between initial PF loss and optimized PF loss	94
6.8	Solution of the switches in the weighted Fixed Reconfiguration case	96
7.1	Fixed Reconfiguration case with a high amount of power generation	100
7.2	A small scale electrical network	104
7.3	Voltage variation (p.u) of the curtailment model on the modified IEEE-33 at T_2	105

9.1	Le graphe sous-jacent	116
9.2	Une configuration réalisable	116
9.3	$\{1,2,3,4\}$ est fusionné en w_0 et $\{5,6,7\}$ en la source	122
9.4	Optimisation dans le cas des courbes de charge et de production	131
9.5	Cas d'une reconfiguration fixe avec un taux de production élevé à un instant donné	134

List of Tables

4.1	Experiments on an agency of SRD	67
5.1	Initial OPs	73
5.2	Results for the switches	74
5.3	OP1 and OP2	74
5.4	Results for OP1 and OP2	74
6.1	Active power load and generation coefficient	89
6.2	Results of the objective function and total cost for the different cases on a modified IEEE-33 bus	90
6.3	The number of manipulations and simulation's time for the different cases on a modified IEEE-33 bus	90
6.4	Results of simulations on the simplified network for OP_1 and OP_2	93
7.1	Results of the small scale electrical network	104
7.2	Power Curtailment model on a modified IEEE-33	105
7.3	Case 1 on a modified IEEE-33 for the relaxation voltage model	106
9.1	État des interrupteurs après élimination des interrupteurs peu impactants . . .	127
9.2	Resultats pour OP1 and OP2	127

Introduction

This thesis focuses on the study of the Distribution Network Reconfiguration (DNR) problem. The DNR problem finds its application in the optimization of electrical distribution networks' performance, reducing power losses and improving network efficiency. Distribution networks are part of power systems, often subject to power losses that result in inefficiency and operational issues. Changing the network's configuration to provide better power flow, minimize losses, and ensure reliable service is a key method for solving these problems; this is the essence of DNR. The DNR problem is NP-complete; thus, determining an optimal configuration is computationally intensive, especially in large-scale networks. This is due to the large search space of possible configurations and the need to satisfy operational constraints such as voltage limits and load balancing. The approach used in this thesis to solve the DNR problem is Mixed Integer Quadratic Programming (MIQP). A comparison between different methods to solve the DNR problem is presented, followed by a justification for using the MIQP approach. The contributions lie in reducing the solver's computational time using this approach to address single-point reconfiguration, considering one operating point. Then, load-curve-based optimization is discussed as a generalization of single-point reconfiguration, considering dynamic loads and productions over time. A comparison between different cases of multiple (dynamic) reconfigurations in this context is presented. The challenges posed by the integration of decentralized generation, which may destabilize the network and complicate the reconfiguration process, are also discussed. Overall, the contributions of this dissertation enhance the solver's computational efficiency while addressing the challenges posed by the high integration of distributed generation, a specific operational issue in large-scale networks.

The thesis is structured to analyze all the techniques based on MIQP, starting from the basic DNR problem in single-point reconfiguration, and progressing to more complex problems like multiple reconfigurations and addressing the challenge of high integration of decentralized generations, with solutions such as power curtailment and voltage relaxation.

We will present the characteristics of the electrical power system of France, its components, and the roles of Distribution System Operators (DSOs) in controlling the network.

Chapter 1

Distribution Networks and Distribution System Operators: Structure and Exploitation

The French electrical distribution network comprises a complex infrastructure that ensures the efficient supply of services across the country. At its core, this network includes diverse components, each playing a pivotal role in the delivery process. Distribution centers are strategically placed throughout the country, supported by a comprehensive network of transportation modes including roads, rail, and waterways. Additionally, operating software and real-time tracking solutions are seamlessly integrated into the network, enhancing efficiency and responsiveness. These components form the backbone of the French distribution network, facilitating the transportation of electricity to meet the varied needs of consumers and businesses alike.

1.1 Electrical power system of France

The French electrical power system is designed to meet the nation's energy demands while fulfilling the requirements of reliability, sustainability, and economic efficiency.

1.1.1 Main characteristics

Mix of Generation Sources The French power system benefits from a diverse mix of generation sources, encompassing nuclear, hydroelectric, renewable, and thermal power plants. Particularly, nuclear power plays a role, significantly contributing to the country's electricity production. In this context, a part of the renewable energy can be controlled or regulated to match the demands with a low carbon energy.

High Reliance on Nuclear Power France has a longstanding commitment to nuclear energy. France derives about 70 % of its electricity from nuclear energy, with a significant portion of its electricity generated by numerous nuclear reactors. This strategic reliance on nuclear power positions France as one of the leading countries in low-carbon energy production. We will make a point about the different levels of the french electrical network before getting into the components of the electrical distribution network that is the stage of this thesis's applications.

1.1.2 Grid infrastructure

High Voltage Transmission Network The high voltage transmission network in France ensures the effective and reliable transportation of electricity across the country. Operated by the national electricity transmission company, Réseau de Transport d'Électricité (RTE), the network displays a meshed construction of transmission lines, substations, and control systems. Operating at various voltage levels, with Extra High Voltage (EHV) and Ultra High Voltage (UHV), this network efficiently conducts power from different generation sources to regional distribution networks. A crucial element of the broader European interconnected grid, the French high voltage transmission network improves cross-border electricity exchanges, improving grid stability and power optimization. Innovations in control systems, such as Supervisory Control and Data Acquisition (SCADA) and Energy Management Systems (EMS), emphasize its flexibility, while operating advancements creates challenges like line power losses and resilience. Moreover, the network integrates renewable energy sources, lining up with France's goals for a low-carbon energy future. The voltage level of this network in France is referred as HV ranging from 50 kilovolts (kV) and above.

Distribution network The distribution networks in France is as adaptive systems, with the role for the localized delivery of electricity to end-users across different regions. Managed by Distribution System Operators (DSOs) such as Enedis and SRD, the distribution network in France follows a hierarchical structure encompassing various components, including distribution lines, transformers, substations, and smart grid technologies. Actually, the SRD distribution network is integrating smart grid technologies enable real-time communication, facilitating precision, fault detection, and adaptation to dynamic load

variations. The French distribution network continues to expand to accommodate the increasing integration of renewable energy sources, demand-side management, and advanced metering infrastructure. Through technological advancements and regulatory frameworks, the distribution networks in France exemplifies a smart and resilient system within the realm of modern electrical infrastructure. The voltage level of distribution networks in France is referred as Mid voltage (MV), ranging from 20 kV to 50 kV, and it is responsible for distributing energy from transmission substations to distribution substations.

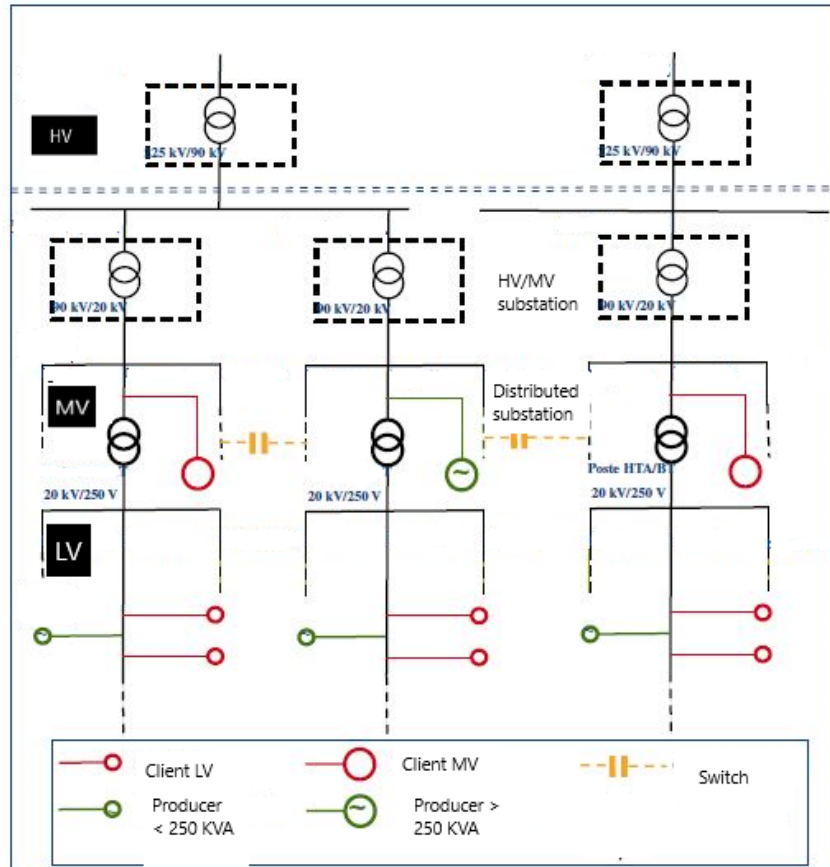


Figure 1.1: The french electrical network

Regional Distribution Networks

Regional distribution networks ensure the localized delivery of electricity to end-users. These networks are structured hierarchically, encompassing primary, secondary, and tertiary levels, each serving specific geographical areas. They are operated by distribution system operators on a voltage level typically up to 400 V.

1.2 Introduction to distribution networks

In the world of electrical power systems, distribution networks are responsible for delivering the electricity from the high voltage transmission network to end-users. They play

a pivotal role in linking the centralized power generation and the different points of consumption. We will present their different levels, then we will introduce their components and their importance.

1.2.1 Levels of the Distribution Network

The distribution networks in France is composed of three main levels. These levels depends on their voltage range.

- Primary Distribution:

At the primary distribution level, high-voltage electricity from the transmission system is decreased to medium voltage (generally between 6 kV and 20 kV) at primary substations. This level of the network covers large geographic areas and serves as the first point of distribution to secondary substations.

The primary distribution networks level contain producers such as solar panels. They also contain decentralized energy sources into the grid. The producers generate electricity locally and can contribute to the primary distribution network. These producers include residential solar panels, small wind turbines, and other renewable energy sources that feed into the grid, helping to stabilize and diversify energy supply while reducing dependence on centralized power plants.

- Secondary Distribution:

The secondary distribution level furthermore decreases the voltage from medium voltage to low voltage (230/400 volts) for final release to end-users. This level of the network involves a network of upward and underground lines, beside secondary substations founded closer to consumers premises.

- Tertiary Distribution:

Tertiary distribution relates to the final level of the network. It is composed from two levels where electricity is delivered directly to consumers' premises. This level encompasses the last-mile connections, including service ensuring electricity reaches individual homes.

Historically, the energy sources was centralized, where the distribution network received energy from the transmission system. Now, the number of decentralized producers is increasing at the primary and secondary distribution levels. This imposes additional challenges for the DSOs in order to manage these decentralized energy sources.

1.3 Electrical engineering

In this section, the basic notions of electrical engineering are presented. These notions are essential to emphasize how much these parameters are important to the optimization and operation of distribution networks. Moreover, a clear understanding for these parameters is essential for modeling distribution networks while imposing electrical constraints. More

precisely, it influences decisions related to network reconfiguration, which is the method employed in this thesis.

In electrical engineering, the current I is the flow of electric charge per unit of time through a conductor. It is measured in amperes (A).

1.3.1 Definition of Alternating Current (AC)

Alternating current (AC) is an electric current that periodically reverses direction, unlike direct current (DC), which flows only in one direction. The most common form of AC is a sinusoidal waveform, characterized by its *amplitude*, *frequency*, and *phase*.

The voltage U represents the electrical potential difference between two points within the distribution network. In electrical engineering, voltage is a parameter that is calculated at each vertex (bus) in the network to ensure proper operation and stability. It is essential to impose limits on voltage variation at each vertex to maintain network stability. In fact, during periods of high power generation, there can be an increase in voltage levels within the network. This elevation in voltage can lead to instability if not properly managed. Therefore, it is necessary to monitor and control voltage levels to prevent potential issues such as equipment damage or grid instability. In France, the voltage can vary up to $\pm 10\%$ from the nominal voltage.

A sinusoidal AC voltage can be represented as:

$$V(t) = V_{\max} \sin(\omega t + \phi)$$

where:

- $V(t)$ is the instantaneous voltage at time t .
- $V_{\max}$ is the peak voltage (maximum amplitude).
- ω is the angular frequency in radians per second, related to the frequency f by $\omega = 2\pi f$.
- ϕ is the phase angle in radians.

Similarly, the current can be represented as:

$$I(t) = I_{\max} \sin(\omega t + \theta)$$

where:

- $I(t)$ is the instantaneous current at time t .
- $I_{\max}$ is the peak current (maximum amplitude).
- ω is the angular frequency (the same as that of the voltage for a given AC system).
- θ is the phase angle of the current.

1.3.2 Phase Difference (Dephasage)

The phase difference between the voltage and the current in an AC circuit is:

$$\Delta\phi = \phi - \theta$$

This phase difference, indicates how much the current waveform is shifted relative to the voltage waveform. An import difference phase can lead to voltage destabilization and higher power losses in the network.

- If $\Delta\phi = 0$, the voltage and current are said to be in phase.
- If $\Delta\phi \neq 0$, there is a phase difference:
 - $\Delta\phi > 0$: The current lags behind the voltage.
 - $\Delta\phi < 0$: The current leads the voltage.

1.3.3 Impedance and Phasor Representation

In AC circuits, impedance (Z) is used to represent the combined effect of resistance (R), inductance (L), and capacitance (C) on the current and voltage. Impedance is a complex quantity given by:

$$Z = R + jX$$

where:

- R is the resistance.
- X is the reactance ($X_L = \omega L$ for inductors and $X_C = \frac{1}{\omega C}$ for capacitors).
- j is the imaginary unit ($j^2 = -1$).

Using phasor representation:

- Voltage: $\mathbf{V} = V_{\max} e^{j\phi}$
- Current: $\mathbf{I} = I_{\max} e^{j\theta}$

The phase difference can be visualized using phasor diagrams, where phasors are rotating vectors representing the magnitude and phase of AC quantities.

1.3.4 Power in AC Circuits

Active power, denoted as P , represents the actual energy transferred to the load and converted into useful work within electrical systems. It is the component responsible for performing work, generating heat, or executing mechanical tasks. Active power is consumed by electrical loads or supplied by power generation sources.

Reactive power, denoted as Q , represents the exchange of energy between sources and loads without performing useful work in electrical systems. It arises due to the presence

of reactive elements such as capacitors and inductors in conductors (lines), which cause phase shifts between voltage and current.

Unlike active power, which produces useful work, reactive power does not perform direct mechanical or heating tasks. Instead, it facilitates the maintenance of voltage levels and assists in the operation of capacitive loads.

In electrical engineering, the consideration of reactive power in the network is essential due to its impact on voltage levels at each vertex. It is measured in volt-amperes reactive (VAR) and plays a crucial role in power system analysis and design, particularly in maintaining system stability and reliability.

Apparent power, denoted by S is the total power through a line (u, v) , expressed within the active and reactive power. S can be expressed as a complex number with $P(u, v)$ and $Q(u, v)$ its real and imaginary part.

The active power (P), reactive power (Q), and apparent power (S) are related by:

$$S = P + jQ$$

where:

- $P = V_{\text{rms}} I_{\text{rms}} \cos(\Delta\phi)$ is the real power (measured in watts, W).
- $Q = V_{\text{rms}} I_{\text{rms}} \sin(\Delta\phi)$ is the reactive power (measured in volt-amperes reactive, VAR).
- $S = V_{\text{rms}} I_{\text{rms}}$ is the apparent power (measured in volt-amperes, VA).
- V_{rms} and I_{rms} are the root mean square values of voltage and current, respectively.

Now, we will present the loads and generations with their definitions and roles. They are essential concepts in the field of electrical engineering and power systems.

1.3.5 Load

Load refers to the amount of electrical power consumed by devices, equipment, or systems within an electrical network. These devices are referred to as load points. It represents the demand for electricity and encompasses various types of electrical loads, including residential, commercial, industrial, and institutional loads. It is important to note that the loads considered in this thesis pertain to the primary distribution. We will observe that the loads utilized are equivalent loads localized in the primary distribution area of the distribution network. Electrical loads are categorized as either active loads, which consume active power (measured in watts), or reactive loads, which consume reactive power (measured in volt-amperes reactive or VARs). In this thesis, loads are also referred to as *consumers*.

1.3.6 Generation

Generation is the process of producing electrical power from various sources, such as fossil fuels, renewable energy, nuclear energy, or hydroelectricity. Distributed generation refers to the generation of electricity for on-site use, rather than transmitting energy over the electric grid from a centralized facility. In this thesis, we focus on distributed generations, which are categorized into renewable generation sources like solar, wind, hydro, and biomass. We refer to them in this thesis as *distributed generation*, or *producers*.

For the SRD network, all distributed energy sources are renewable energy sources, namely wind and photovoltaic installations, hydroelectric power stations, and methanization plants. Wind farms, hydroelectric power plants, and methanization plants inject their produced power directly into the HV network; consequently, these installations can be considered as sources of energy in their own right. In fact, these sources are able to supply consumers neighboring these installations.

1.4 Components of the Distribution Network

The distribution network in France comprises several essential components, including:

1.4.1 Switch

In electrical engineering, a switch is an essential electrical device utilized to interrupt or establish electrical connections within a network. It governs the flow of electricity by permitting or obstructing the current flow through a circuit. Switches can be broadly categorized into two types: controllable switches and non-controllable switches.

- **Controllable switches:**

These switches can be manipulated or controlled by an operator to change their state, i.e., to open or close the circuit. Operators have the ability to remotely control controllable switches, allowing for dynamic adjustments in the network configuration to meet operational requirements.

- **Non-controllable switches:**

Unlike controllable switches, non controllable switches cannot be remotely manipulated by operators. Their states remain fixed and cannot be altered from a remote location. Moreover, they require a manual action to be activated.

In this thesis, it is assumed that the current passing through a switch does not incur losses in terms of active or reactive power. This assumption implies that the resistance of the switch is considered negligible, and therefore, the switch does not dissipate power as heat when conducting current.

In subsequent sections of the thesis, the control mechanisms for switches by operators will be discussed, along with an analysis of the impact of switch control on network

efficiency and adaptation to varying operating conditions. Understanding the behavior and control of switches is crucial for optimizing network performance and ensuring reliable operation in electrical systems.

1.4.2 Transformers

Transformers serve as vital components within electrical distribution networks, facilitating voltage transformation essential for efficient power distribution. Comprising primary and secondary winding coils wound around a laminated iron core, transformers enable the adjustment of voltage levels while preserving frequency. Step-up transformers elevate voltage for long-distance power transmission, thereby minimizing transmission losses, while step-down transformers decrease voltage to safe levels suitable for end-users. With a variety of types including distribution, power, autotransformers, and instrument transformers, each tailored to specific applications, transformers hold significant importance in electrical engineering.

Despite their efficiency, transformers are subject to losses. Proper maintenance is essential to ensure continuity and reliability in transformer operation. From their essential role in voltage regulation to their contribution to energy efficiency, transformers remain indispensable in modern electrical distribution systems. We will present now the different types of transformers.

1.4.3 Transmission substation (High Voltage/Medium Voltage transformers)

In distribution networks, High-voltage/Medium-voltage (HV/MV) transformers receive the energy from the transmission network to the distribution network. They play a crucial role which convert energy from high-voltage transport networks to medium-voltage distribution networks. These transformers typically step down the upstream voltage levels, which are commonly around 90 kV, to downstream voltage levels of approximately 20 kV. Referred to as "transmission substations," these facilities serve as the primary source of energy for the distribution network, functioning as power supply substations.

1.4.4 Distributed substation (MV/LV transformers)

A distributed substation, also known as a distribution substation, plays a critical role in an electrical distribution network. It serves as a key facility responsible for transforming and distributing electricity from medium voltage (MV) levels to lower voltage levels suitable for local distribution to end-users. Typically operating at MV levels ranging from 2 kV to 50 kV, distributed substations facilitate the distribution of power to consumers within a specific area.

The lower voltage network is not reconfigurable. In contrast, we are interested to reconfigure the medium voltage network (MW) where the SRD distribution network has from 7000 to 8000 switches. Therefore, the distributed substations are considered as a

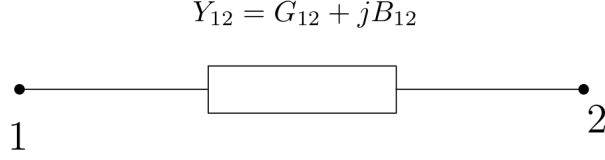


Figure 1.2: The admittance model of a line (1, 2)

load or generation in the medium voltage network, clustering the loads and generation of the lower voltage network.

In this context, distributed substations are considered either as loads or distributed generations. Consequently, the focus of this work will be on the distribution network between transmission substations and distributed substations. These distributed substations, also referred to as MV/LV substations, are important in delivering power at low voltage (LV) levels, where LV denotes the low-voltage level in an electrical distribution system.

The low-voltage level (LV) typically ranges from 220 Volts (V) to 400 volts (V) for single-phase connections and up to 690 volts (V) for three-phase connections. This voltage level is commonly utilized for supplying electricity to individual consumers, including residential, commercial, and small industrial customers, as it is well-suited for typical applications.

1.4.5 Distribution Lines

Distribution lines, essential components of electrical distribution networks, have the role of transporting electricity from substations to end-users. These lines, whether overhead or underground, are exposed to power losses, a phenomenon that needs serious consideration in network operation and design.

The distribution line is characterized by its *impedance* Z , which is a complex number composed of the *resistance* R in Ohms and its *reactance* X in Ohms. We have $Z = R + jX$, where R and X are the real and imaginary parts of Z . Another representation for a distribution line, which is used in power flow simulations (to be defined in the following sections), is called the *admittance* Y . We have $Y = 1/Z$. For a series circuit, which we will deal with in this thesis, we have: $Y = G + jB$, where G is the real part of Y called the *conductance*, and B is the imaginary part of Y called the *susceptance* (see Fig. 1.2). These parameters depend on the physical characteristics of the line. For example, resistance losses depend on the conductor's material and increase with the length of the distribution line and the magnitude of current flowing through it.

Power Losses in Distribution Lines (Joules losses)

Power losses (Joules losses) in distribution lines proceed primarily due to two mechanisms: resistance losses and dielectric losses. The power losses is defined by: $P_{losses} = R \cdot I^2$

- Resistance Losses: As electricity flows through the conductors of distribution lines, it encounters resistance, leading to the conversion of electrical energy into heat. For example, the SRD network has more than 7000 km of distribution lines.

- Dielectric Losses: In underground cables, dielectric losses occur due to the capacitance between the conductors and the surrounding soil or insulating material. These losses result in the conversion of electrical energy into heat within the cable insulation.

Impact of Power Losses

Power losses in distribution lines have many impacts on network efficiency, reliability, and cost:

- Energy Efficiency: Power losses reduce the efficiency of electricity distribution, leading to wastage of energy and increased consumption of primary energy resources.

- Voltage Regulation: Voltage drop along distribution lines due to Joules losses can result in voltage variations at the load end, affecting the performance of electrical equipment and appliances.

- Operational Costs: Power losses contribute to operational costs for utilities, including charges related to energy generation, transmission, and distribution. Minimizing losses is consequently essential for optimizing the cost of operations in the distribution networks.

Directions

As distribution networks continue to integrate renewable energy, electric vehicle charging infrastructure, and smart grid technologies, the management and reduction of power losses will remain a key focus area. Emerging technologies such as distributed energy resources and advanced grid management techniques offer promising avenues for reducing losses and improving network efficiency. Moreover, ongoing research and development efforts aim to enhance the performance of distribution line materials, minimizing losses and maximizing the value of electrical distribution systems. By addressing the challenge of power losses proactively, stakeholders in the electricity sector can achieve significant improvements in energy efficiency, reliability, and cost-effectiveness, ultimately benefiting both utilities and end-users.

1.5 Structure and exploitation

After delving deeper into the complexities of distribution networks, it becomes evident that their efficiency and resilience depend not only on individual elements but also significantly on their overall topology. Transformers, substations, and distribution lines form the backbone of these networks; however, it is their interconnection and communication that determine the network's operational characteristics. Transitioning from the definition of these fundamental components, the focus shifts to the topology of distribution networks, which can be classified into radial and meshed configurations. These distinct configurations play a crucial role in adjusting the network's reliability, flexibility, and performance. Let us explore how the radial and meshed arrangements influence electricity flow, fault tolerance, and operational strategies within distribution networks.

In order to model the distribution network, the graph theory is used. It provides a framework for understanding, analyzing and optimizing the electrical networks. The essential notions of the graph theory are presented in the next section.

1.5.1 Graph theory

Generalities

In this section, all definitions are taken from [Die12]. All graphs studied are finite graphs. Formally, a *graph* is a pair $G = (V(G), E(G))$ where $V(G)$ is the set of vertices of G and $E(G)$ is the set of its edges. Let $G = (V(G), E(G))$ and $G' = (V(G'), E(G'))$. G' is called a *subgraph* of G if $V(G') \subseteq V(G)$ and $E(G') \subseteq E(G)$. If $S \subseteq V(G)$, we denote by $N(S)$ the set of neighbours of each $x \in S$. Let $P = (V(P), E(P))$ be a subgraph of a graph G . P is called a *path* if $V(P) = \{x_0, \dots, x_k\}$ and $E(P) = \{x_0x_1, \dots, x_{k-1}x_k\}$ where the vertices x_0 and x_k are linked by P . We often refer to a path by the natural sequences of its vertices, that is to say, $P = x_0 \dots x_k$ and we call P a path from x_0 to x_k . If $P = x_0 \dots x_{k-1}$ and $C = P \cup x_{k-1}x_0$ with $\{x_{k-1}, x_0\} \in E(G)$, C is called a *cycle*. A non-empty graph G is called *connected* if any pair of its vertices are linked by a path in G . An *acyclic* graph is a graph without cycles. A *forest* is an acyclic graph. A connected acyclic graph is called a *tree*. An *oriented graph* (or *digraph*) $G = (V(G), A(G))$ is a graph where each edge has a direction. This edge is called an *arc*. $A(G)$ is the set of arc of G . For a vertex v , a *direct predecessor* of v is a vertex u such that there exists an arc $(u, v) \in A(G)$. a *direct successor* of v is a vertex u such that there exists an arc $(v, u) \in A(G)$. A *leaf* in a graph is an external or terminal vertex in the graph. It refers to a vertex that has only one edge connected to it.

Radial Network

In graph theory, a radial network is a tree structure, where one central vertex (or substation) is the root of the tree, and all other vertices (or load points) are connected to it through directed branches (or transmission lines). It is worth to say that the word radial is not common in the graph theory's bibliography. But it is common in the bibliography of electrical power system.

Each vertex in a radial network has one and only path leading to the central vertex, resulting in an unidirectional flow of electricity. We will suppose that a radial graph has a tree-like structure and connected. Therefore, it is a connected graph, that contains no cycle (see Fig. 1.3).

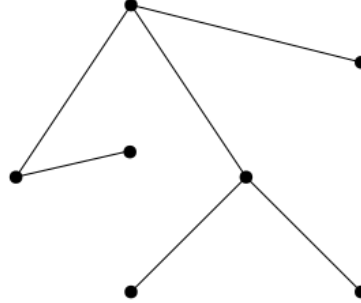


Figure 1.3: A radial graph

Distribution systems operate in a radial regime for several reasons, including effectiveness and reliability. Radial networks are highly scalable, allowing for easy modification of topology to accommodate different incidents. Moreover, while traditionally designed for unidirectional power flow from the substation to the loads, radial networks can facilitate bidirectional power flow by changing the state of branches to provide an alternative path to the substation while maintaining radially. This introduces more efficiency to the control of the network, especially with the high integration of distributed generations.

Meshed Network

In contrast, a meshed network is characterized by the presence of two or more paths each every two vertices forming cycles within the network (see Fig. 1.4). Each vertex in a meshed network can be connected to multiple other vertices, allowing for supplementary paths and multiple ways of connection between substations and load points.

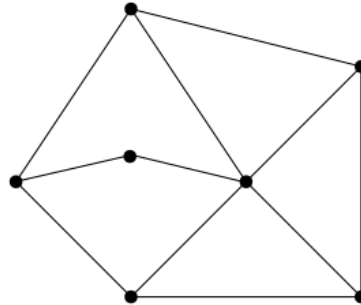


Figure 1.4: A meshed graph

Meshed networks provide increased reliability and fault tolerance compared to radial networks, as they offer alternative paths for electricity flow in the event of line failures or

disruptions. From a graph theory perspective, a meshed network can be represented as a graph that contains at least one cycle, forming an interconnected topology.

Just as graphs are a powerful tool for modeling complex interactions in various domains, they find practical applications in understanding the behavior of the topology of electrical distribution networks. In this context, the notions of meshed and radial configurations take center stage, explaining different network architectures with deep implications for reliability and efficiency. Moreover, they permit modification of the network structure by opening and closing graph cycles, which is done by opening and closing switches (manual or controllable), allowing the 'cut' of a power line.

In the following section, we will turn our attention to the key aspect of network supervision and control. While the topology determines the physical structure of the network, efficient supervision guarantees its effective operation and management in real-time.

1.5.2 Distribution system operators (DSO)

As we have seen, the distribution network is composed of different elements, and it is important to know their specifications. Moreover, we have seen that the network can be exploited in different ways for its normal operation during incidents. Therefore, it is crucial for the network operator to have control over the network, while following its evolution especially with dynamic loads and generations.

The role of DSOs

Distribution System Operators (DSOs) have the responsibility of managing the last leg of the power supply chain — the distribution network. This network, considered as the heartbeat of the power system, is a web of transformers, switches, and lines that connect communities and regions. DSOs have a pivotal role in optimizing the performance of this network, adapting to varying demand patterns, managing renewable energy sources, and strengthening the system against unexpected challenges.

1.5.3 Methods of control for DSOs

The methods of control used by Distribution System Operators (DSOs) encompass a range of strategies and technologies that ensure the reliable and efficient operation of the distribution network. Some main methods of control include:

Network monitoring

Network monitoring, with cartography as an integral element, is essential for guaranteeing the efficient and reliable operation of electrical distribution networks. Cartography, or mapping, provides spatial visual representations of the distribution network's physical format, including the location of substations, distribution lines, switches, and other network components. This spatial understanding improves asset management by associating

control data with specific assets on the map, aiding in cautious maintenance and planning for network enhancement. While monitoring, cartography assists in fault localization by identifying anomalies within the network, leading response efforts. In the _Figure, a portion of the SRD network taken from the cartography tool is illustrated. The SRD network is divided into 8 agencies. It is worth noting that for a better way of monitoring, Cartography may be insufficient. This is because Cartography relies on static diagrams to represent the network's spatial layout, thus not collecting real-time data that can be changed with different conditions. Moreover, it does not enable operators to respond to network disturbances promptly. Another tool for monitoring used by DSOs is discussed in the following section.

Supervisory Control and Data Acquisition (SCADA) Systems

SCADA systems provide real-time monitoring and regulation of various components within the distribution network, including substations, switches, and distribution lines. These systems gather data on network parameters such as voltage, current, power flow, and equipment status, allowing operators to monitor network conditions and locate abnormalities. SCADA systems permit operators to remotely control equipment, such as switches and voltage regulators, to optimize network performance and respond to different conditions. Moreover, they allow the modification of the topology by changing the state of the switches depending on the given conditions.

Load Management and Demand Response

DSOs apply load management designs to balance supply and demand within the distribution network. Demand response programs allow DSOs to adapt electricity consumption by motivating consumers to reduce or shift their consumption during peak periods. Advanced metering infrastructure (AMI) and smart grid technologies allow DSOs to interact with customers and remotely control equipment to balance load profiles and optimize network performance.

Voltage Regulation and Reactive Power Control

DSOs deploy voltage regulators, capacitor banks, and other reactive power compensation devices to maintain voltage levels at their limits, especially during peak periods, and ensure power quality within the distribution network. These devices help control voltage changes, enhance system stability, and minimize losses related to reactive power flow.

1.6 Load flow

The Load Flow Analysis, also known as power flow analysis, is a fundamental and crucial aspect of electrical power system analysis. It ensures that voltage magnitudes and phase angles at all buses in the system remain within acceptable limits to maintain system stability and reliability while guaranteeing the balance between generations and loads to prevent overloading of system components. This section aims to provide a comprehensive overview of load flow analysis employed in analyzing and understanding the steady-state behavior of power systems. We will mention methods that are used for any topology (meshed, radial ..).

1.6.1 Methodology

The goal of power flow equation is to obtain the active and reactive power in function of the voltage and admittances. In this section, we will show how the power flow equations are obtained. These equations are derived from the First Kirchhoff law on each vertex.

For a vertex k , let I_k be the total current at k . The Kirchhoff current at k is defined by: $I_k = \sum I_{ki}$

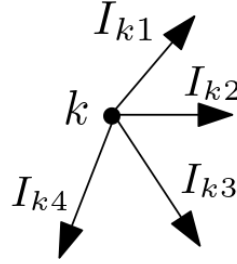


Figure 1.5: Kirchhoff current at k

I_{ki} is the current flowing from k to i (see Fig. 1.5). The Ohm's law applied on the admittance diagram (or representation) of a line from k to i is: $I_{ki} = y_{ki} \cdot (V_k - V_i)$ where y_{ki} is the admittance of the line ki and V_k is the voltage at vertex k .

By applying the Ohm's law of the admittance diagram, we have:

$$\begin{cases} (V_k - V_i) \cdot y_{ki} & \text{if } k \neq i \\ V_k \cdot y_k & \text{if } k = i \end{cases}$$

Therefore, the expression of the current at vertex k is:

$$\begin{aligned} I_k &= \sum_{k \neq i} (V_k - V_i) \cdot y_{ki} + V_k \cdot y_k \\ &= V_k \left(\sum_{k \neq i} y_{ki} + y_k \right) - \sum_{k \neq i} V_i \cdot y_{ki} = Y \cdot V \end{aligned}$$

Y is the $N \times N$ admittance matrix (N number of vertices of the network) and V is the voltage's vector ($N \times 1$).

Thus, I is a $N \times 1$ matrix and for each bus k (each element of the matrix I), the current I_k is: $I_k = \sum_{i \in N} Y_{ki} \cdot V_i$ with Y_{ki} the elements of the admittance matrix Y .

The complex apparent power at a bus k is:

$S_k = V_k \cdot I_k^*$ with I_k^* the conjugate of I_k . The polar form of voltage at a bus k is: $V_k = |V_k| \angle \theta_k$ where θ_k is the phase angle of the voltage at bus k . By substitution of I_k in S_k , we obtain:

$$\begin{aligned}
S_k &= V_k \cdot \left(\sum_{i \in N} Y_{ki} \cdot V_i \right)^* \\
&= V_k \cdot \sum_{i \in N} Y_{ki}^* \cdot V_i^* \\
&= V_k \cdot \sum_{i \in N} (G_{ki} + i \cdot B_{ki})^* \cdot (|V_i| \angle \theta_i)^* \\
&= V_k \cdot \sum_{i \in N} (G_{ki} - i \cdot B_{ki}) \cdot (|V_i| \angle -\theta_i) \\
&= V_k \cdot \sum_{i \in N} (G_{ki} - i \cdot B_{ki}) \cdot (|V_i| \angle -\theta_i) \\
&= |V_k| \cdot \angle \theta_k \cdot \sum_{i \in N} (G_{ki} - i \cdot B_{ki}) \cdot (|V_i| \angle -\theta_i) \\
&= \sum_{i \in N} |V_k| |V_i| \cdot \angle(\theta_k - \theta_i) \cdot (G_{ki} - i \cdot B_{ki}) \\
&= \sum_{i \in N} |V_k| |V_i| \cdot \cos(\theta_k - \theta_i) - j \cdot \sin(\theta_k - \theta_i) \cdot (G_{ki} - i \cdot B_{ki})
\end{aligned}$$

On the other side, we recall that the complex apparent power S_k at a vertex k is: $S_k = P_k + j \cdot Q_k$ where P_k and Q_k are the active and reactive power at the vertex k . Therefore, we obtain the famous power flow equations by collecting the real and imaginary part of S_k :

$$P_k = \sum_{i \in N} |V_k| |V_i| \cdot G_{ki} \cdot \cos(\theta_k - \theta_i) + B_{ki} \cdot \sin(\theta_k - \theta_i) \quad (1.1)$$

$$Q_k = \sum_{i \in N} |V_k| |V_i| \cdot G_{ki} \cdot \sin(\theta_k - \theta_i) - B_{ki} \cdot \sin(\theta_k - \theta_i) \quad (1.2)$$

The power flow equations are used to calculate the voltage and phase angle on each vertex.

The power flow equations represent the balance of active and reactive power in the system, taking into account the relationships between voltage magnitudes, phase angles, and power injections. These equations are nonlinear because of the presence of trigonometric functions and dependencies on voltage and phase angles.

In those equations, the active and reactive power P_k and Q_k are supposed to be known if the bus is a load bus. If it is a generator bus, it is assumed that the active power generator is known. As a reminder, G_{kj} is the real part of the element in the bus admittance matrix Y_{kj} and B_{kj} is the imaginary part of Y_{bus} . V_k is the voltage at bus k and θ_i is the difference in voltage angle between i_{th} and k_{th} buses. It is worth to say that when it goes to load flow analysis, the topology of the network is needed in order to determines the coefficient of the admittance matrix. Now, we will see the methods that solves these equations.

Load flow methods can solve these nonlinear equations iteratively to find the system's operating points. Various numerical techniques such as Newton-Raphson method, Gauss-Seidel method, and their variants are commonly employed for solving the power flow equations. The Newton-Raphson method is one of them.

1.6.2 Newton-Raphson method

The methods used to identify the different parameters of an electrical work without a specified topology (for example a tree-like topology) are the matricial methods. One of the most known methods is the Newton-Raphson method [SE68] which is an iterative method. In this section, a general description of this method based on the power flow equations is developed.

A function with a single variable

In this section, we will describe the Newton-Raphson method for a non-linear function f for a single variable x . Let x^r be a single root for $f(x)$. The goal is to solve the equation $f(x) = 0$. The Newton-Raphson method considers an initial estimate of the root x_0 . The tangent of $f(x)$ at x_0 will improve the estimation of the root by intersecting x-axis at a point x_1 . This improvement from x_0 to x_1 is called a single iteration of the Newton-Raphson method. The next iteration uses the tangent for $f(x)$ at x_1 to obtain x_2 in the same way (Fig. 1.6). The gradient of the tangent on $f(x)$ is by definition $f'(x)$. But we will use the following approximation in order to determine the intersection between the line tangent and the x-axis. The tangent line on $f(x)$ at x_0 passes by the two points $(x_0, f(x_0))$ and $(x_1, f(x_1) = 0)$. The gradient is then $\frac{f(x_0)-0}{x_0-x_1}$ and then $x_1 = x_0 - \frac{f(x_0)}{f'(x_0)}$ where $f(x_1)$ is approximated to be null. (1.6.2) is generalized as $x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$ for $n \in \mathbb{N}$.

The end process of the iterations is simple. We stop if the standard error estimate $|x_{n+1} - x_n| \leq \epsilon$. Otherwise, we go to the next iteration.

A function with many variables

The goal in this section is to show how the power flow equations in Section 1.6.1 are solved. In (1.1) and (1.2), we suppose that P_k and Q_k at each vertex k are known. They are the amount of active and reactive power at k . The unknown variables remain are V_k and θ_k . So, $P_k = P_k(V_k, \theta_k)$ and $Q_k = Q_k(V_k, \theta_k)$ are two functions of V_k and θ_k .

The resolution of these equations is based on Taylor series around an initial point $(a_1, a_2, \dots, a_n)$ which is resolved by the Newton Raphson method.

$$f(x_1, x_2, \dots, x_n) = f(a_1, a_2, \dots, a_n) + \sum_{i=1}^n \left. \frac{\partial f}{\partial x_i} \right|_{(a_1, a_2, \dots, a_n)} (x_i - a_i)$$

The next step is to linearize (1.1) and (1.2) using Taylor series on $P_k(V_k, \theta_k)$ and $Q_k(V_k, \theta_k)$ around the initial point $(V_k = V_N, \theta_k = 0)$, where V_N is the nominal voltage. The first iteration is supposed to be made on the point $(V_k = V_N, \theta_k = 0)$, where we will the exact value of $P_k(V_k, \theta_k)$ and $Q_k(V_k, \theta_k)$. For the next iteration, we apply the linearization:

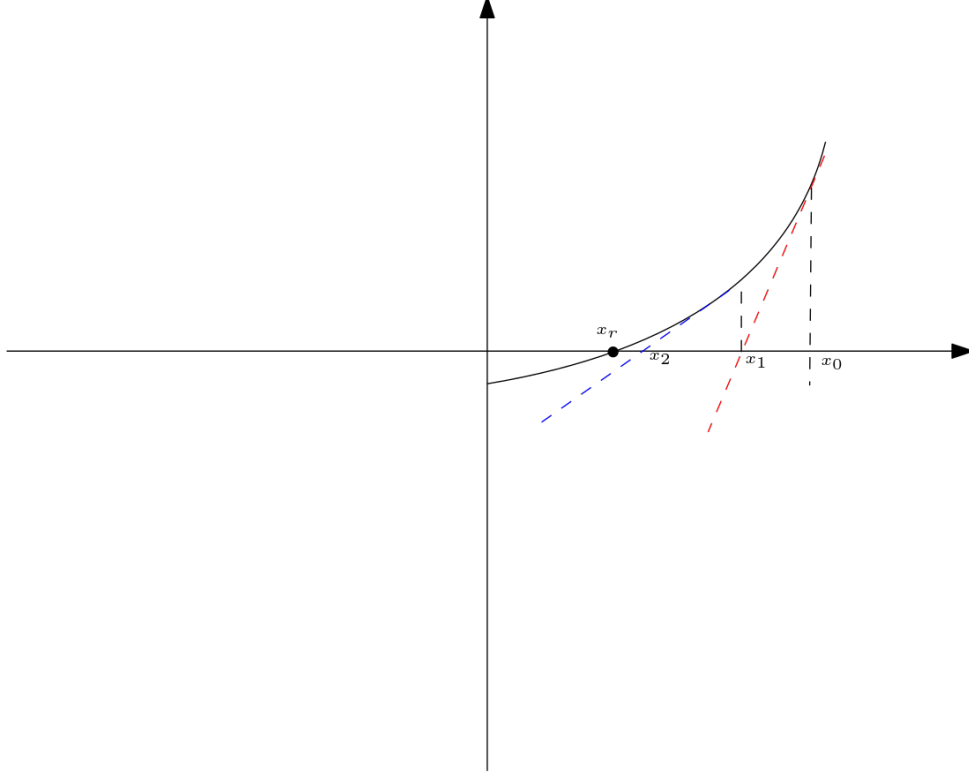


Figure 1.6: Newton-Raphson method on a single variable function

$$P_k(V_k, \theta_k) = P_k(V_N, 0) + \left. \frac{\partial P_k}{\partial V_k} \right|_{(V_N, 0)} (V_k - V_N) + \left. \frac{\partial P_k}{\partial \theta_k} \right|_{(V_N, 0)} (\theta_k - 0) \quad (1.3)$$

$$Q_k(V_k, \theta_k) = Q_k(V_N, 0) + \left. \frac{\partial Q_k}{\partial V_k} \right|_{(V_N, 0)} (V_k - V_N) + \left. \frac{\partial Q_k}{\partial \theta_k} \right|_{(V_N, 0)} (\theta_k - 0) \quad (1.4)$$

Now, The system (1.3) and (1.4) can be solved using matrices methods. We remind that the goal is to find the values of V_k and θ_k .

The Newton-Raphson's method is applied on each iteration. The first iteration was on the initial point $x^{(0)} = (V_k, 0)$ where we will obtain the values of $P_k(x^{(0)})$ and $Q_k(x^{(0)})$. On an iteration k , we need to calculate the Jacobian matrix J and the function value $P_k(x^{(k)})$ and $Q_k(x^{(k)})$ at the point $x^{(k)} = (V_k^{(k)}, \theta_k^{(k)})$. We update then the point using the formula:

$$x^{(k+1)} = x^{(k)} - (J)^{-1} \cdot P_k(x^{(k)})$$

$$\text{Where } J = \begin{bmatrix} \frac{\partial P_k}{\partial V_k} & \frac{\partial P_k}{\partial \theta_k} \\ \frac{\partial Q_k}{\partial V_k} & \frac{\partial Q_k}{\partial \theta_k} \end{bmatrix}$$

This process will stop when $x^{(k+1)}$ converges or become very close to $x^{(k)}$. Then, the values of V_k and θ_k are obtained.

1.7 Optimization

In contrast to iterative methods, an approach exists to assist DSOs in addressing the challenges of selecting the optimal network configuration. In the context of large-scale networks with a high integration of distributed generations, the task of selecting the best network topology while considering the state of switches becomes crucial. This challenge can be referred to as the Distribution Network Reconfiguration (DNR) problem. Optimization techniques are employed to tackle the DNR, formulated with defined objectives and constraints, aimed at identifying the optimal network reconfiguration.

Generally, the key difference between load flow analysis methods lies in their outcomes and applications. Load flow analysis provides the state of a given network, including voltage values at each bus, power flowing through branches, etc., typically using iterative methods. In fact, solving the non-linear load flow equation in a strictly exact way is not feasible. However, when discussing optimization, we refer to changing the topology or state of the network. This cannot be achieved by applying load flow analysis. In contrast, the new topology obtained through optimization can be utilized in power flow analysis to verify various parameters in this new topology, such as voltage limits. Moreover, optimization allows DSOs to take action and make adjustments to the given network. One such action is to modify the network's topology.

In fact, optimization techniques offer flexibility in incorporating various objectives and constraints, while iterative methods are primarily used for load flow analysis. These methods determine the operating condition of an existing network reconfiguration. Iterative methods do not directly change the network topology, while optimization methods can do so. However, iterative methods, such as power flow or load flow analysis, can be integrated into optimization algorithms, either as part of the initialization process or to verify the steady state of solutions found by optimization techniques.

In this section, we will define briefly the problem formulation and we will the conditions to obtain an optimal solution.

1.7.1 Problem formulation

The formulation of an optimization problem is defined by an objective function and constraints on the variables of the problem [BV04]. The objective function represents the optimization criteria, and to solve the optimization problem, one must find the extremum (minimum or maximum) of this function. The constraints are equations representing relations between the variables. An optimization problem P is characterized by its objective function and its set of constraints.

Minimize/Maximize: $f(x)$

$$g_i(x) \leq b_i \quad i \in \{1, \dots, m\}$$

$$h_i(x) = d_i \quad i \in \{1, \dots, p\}$$

x is the vector of variables with n components: $x = [x_1, \dots, x_n]^T$. $f(x)$ is the objective

function (optimization criteria) to be minimized or maximized. $g_i(x)/h_i(x)$ are inequality/equality constraints. m/p is the number of inequality/equality constraints. $b_i/d_i \in \mathbb{R}$. The components of each vector x can be continuous or binary variables.

The format above is the *mathematical programming*. If the objective function f and the constraints are linear, it is *linear programming* [Min08]. In the opposite case, it is a non-linear program. If the objective function f is quadratic and the constraints are linear or quadratic, it is a *quadratic programming* [GLS81]. If the variables are integer, then it is an *integer programming* (IP). If the variables are mixed (binary and continuous) and the objective function is quadratic, then it is a *mixed integer quadratic programming* (MIQP).

Now, we will talk about solutions. A *feasible solution* is a vector x that satisfies the constraints of the problem formulation. An *optimal solution* is a vector x that is the best among all feasible solutions. The goal of an optimization problem is to determine the optimal solution. But, if the problem formulation (objective function or constraints) are not linear, we will obtain a *local optimum*. We will show how an optimal solution is guaranteed.

Let X be an interval.

- A point $x_0 \in X$ is a *local minimum* for a function $Z : X \rightarrow \mathbb{R}$ if and only if there exists a neighborhood $V \subseteq X$ such that $\forall x \in V, Z(x) \geq Z(x_0)$.
- A point $x_0 \in X$ is a *local maximum* for a function $Z : X \rightarrow \mathbb{R}$ if and only if there exists a neighborhood $V \subseteq X$ such that $\forall x \in V, Z(x) \leq Z(x_0)$.
- A point $x_0 \in X$ is a *global minimum* for a function $Z : X \rightarrow \mathbb{R}$ if and only if $\forall x \in X, Z(x) \geq Z(x_0)$.
- A point $x_0 \in X$ is a *global maximum* for a function $Z : X \rightarrow \mathbb{R}$ if and only if $\forall x \in X, Z(x) \leq Z(x_0)$.

Convex set

A subset $X \subseteq \mathbb{R}$ is *convex* if $\forall x, y \in X, \forall \lambda \in [0, 1], \lambda \cdot x + (1 - \lambda) \cdot y \in X$. In other words, for any two points in X , the segment joining them remains in X (see Fig. 1.8).

Convex function

A function $Z : X \rightarrow \mathbb{R}$ is *convex* on X if:

$$\forall x, y \in V, \forall t \in [0, 1], z(tx + (1 - t)y) \leq tz(x) + (1 - t)z(y).$$

The following theorem ensures that each optimum obtained is a global optimum. So, if the problem formulation respects this theorem, we can guarantee the optimality of the solution.

Theorem 1 *Let P be an optimization problem. If the constraints and the objective function are convex, then each local optimum is a global optimum [Dah97].*

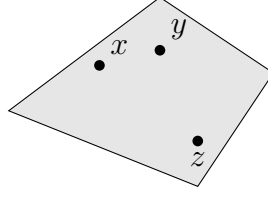


Figure 1.7: An example of a convex hull.

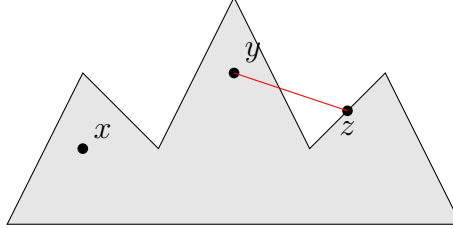


Figure 1.8: An example of a non-convex hull: there exists a segments joining y and z that lies outside the hull

1.8 Conclusion

In conclusion, load flow analysis requires knowledge of the network topology, while network reconfiguration by DSOs necessitates optimization methods to identify the best solution among various switch configurations. Formulating the Distribution Network Reconfiguration (DNR) problem allows for an optimal solution if the objective function and constraints are convex. This thesis relies on a convex model for the DNR problem, and its contributions based on this model will be outlined later.

In the next chapter, we will introduce the context of the thesis and the Labcom project that is undertaken in collaboration between the LIAS Laboratory and SRD. We will describe briefly this project and its different axis of work.

Chapter 2

Context and Thematic: Labcom Alienor

The modernization of the electricity system urges with the high integration of renewable energies in the distribution networks. In fact, it has become essential to dynamically manage the energy flows. Smart grids technologies are deployed in the French and European electrical networks along with data valorization. The DSOs will be able to act in the electrical system with the integration of Next-generation Information and Communication Technologies (NICT). This leads to efficient, economically viable, and safe electricity delivery.

It is in this context that the SRD company and the LIAS laboratory decided to combine their expertise to jointly set up the ANR @LIENOR Joint Laboratory (LabCom) (Laboratory for the Integration of New Energies and Optimization of Networks). This joint laboratory constitutes a continuation of a partnership which had already resulted in the development of a prototype IMAGE tool (Intelligent Management and Energy Management system) which optimizes operating schemes over a period or time horizon. The @LIENOR LabCom is essential not only to the continued integration of ENR, but also allows the IMAGE tool to be industrialized to make it applicable and functional in any industrial environment by adding a stochastic and dynamic approach that considers the variable and intermittent nature of both consumption and ENR production.

SRD

As the fifth-largest electricity distribution network operator in France, SRD develops, operates, maintains, and modernizes nearly 12,000 km of electricity network and nearly 150,000 delivery points in the department of Vienne (86). Vienne is a landlocked department in the French region of Nouvelle-Aquitaine. SRD is committed among local distribution companies to the deployment of smart meters, contributing to the development of energy transition and the renewable energy. Moreover, SRD confirms its commitment in R&D, particularly in data management.

Its missions consist in:

- Maintain and maintain the distribution network works
- Exploit the distribution network
- Design, build and ensure project management of the distribution network in order to guarantee its safety, reliability and efficiency
- Conclude and manage the concession contract
- Ensure access to distribution networks under objective, transparent and non-discriminatory conditions
- Ensure the metering of distributed energies necessary for the performance of its missions (supply, installation, control and maintenance of meters)
- Operating in rural areas. A rural area is a geographical area that is majorly dominated by low population density, extensive open land areas, and limited infrastructure. In most cases, these areas are dominated by agriculture, forestry, and other natural resource-based industries. If compared to urban areas, the rural zones usually have fewer residential buildings, commercial establishments, and public services. The pace of life is slow in rural areas, and community structure is often closer, which explains the involvement of SRD in operating the renewable energy like wind turbines etc.

LIAS

Established on January 1, 2012, The LIAS (Laboratoire d’Informatique et d’Automatique pour les Systèmes) is the result of merging the LAII (Laboratoire d’Automatique et d’Informatique Industrielle) and the LISI (Laboratoire d’Informatique Scientifique et Industrielle). Contributing in the disciplines of Computer Science, Automation, and Electrical Engineering, the laboratory brings together 40 faculty members from CNU¹ sections

¹The National Council of Universities is the national body that oversees the recruitment process and career progression of academic staff at French universities.

27, 61, and 63 in those disciplines. The affiliated institutions for this research unit are the two engineering schools ISAE-ENSMA (Ecole Nationale Supérieure de Mécanique et d'Aérotechnique) and ENSIP (École Nationale Supérieure d'Ingénieurs de Poitiers, a component of the University of Poitiers). These two engineering schools contribute to a strong scientific focus areas to the laboratory: transport, energy, and environment.

The LabCom @LIENOR addresses two of the three priority areas of the supervisory establishments. While rooted in fundamental aspects, LIAS, through its applications, naturally extends to the SPI (Engineering Sciences) sector. Whether in new modes of propulsion, energy management, water treatment, computer modeling of complex systems, or the optimization of real-time systems, the disciplinary complementarities of Automation, Electrical Engineering, and IT add value to the processing of these applications, all of which are related to engineering.

Axes of Labcom

The different axes of The LabCom @LIENOR are presented in this section. These axis are linked in a way that the Image tool is industrialized. Each axis is led by two managers: a faculty member and a permanent SRD staff member.

Axis 1 - Upgrading the optimization

This thesis is lied in this axis. The computational time is the main problematic along with upgrading the optimization model that has been proposed in a previous CIFRE² thesis in the context of the Labcom @LIENOR. In fact, a network like that of SRD comprises thousands of switches enabling the configuration of the operating plan. This large number of switches will have an impact on the computational time to solve the optimization model. Each switch will be represented as a binary variable that takes value 1 or 0. The resolution techniques in this case take a larger computational time than the case where all variables are not binary. For that reason, the reduction of the computational time is crucial.

On the other hand, the upgrading of the existing optimization model in terms of adding additional constraints has been developed. The taking in account of the reactive power will make the calculation of the voltage variation more realistic. On the other hand, a counter example has been identified where the obtained solution does not present an acyclic graph (graph without cycles) in the case of a strong production.

Finally, the upgrading of the optimzation in terms of taking in account the high integration of decentralized productions is presented. The power curtailment consists in cutting the production from the network in case of a high amount of productions of the different type of decentralized generations (renewable energy, etc.). The power curtailment prevents from the high elevation of the voltage in the desired solution and it is a tool to improve the resilience and the stability in the context of reconfiguring the network's topology.

Axis 2 - Forecast module

The DSO needs to predict both consumption and production to maintain the stability and reliability of the grid through the balance of supply and demand, voltage levels, or grid outages. More accurate forecasts would lead to enhanced operational efficiency through planning maintenance and allocating resources more effectively. Proper forecasting is also critical in terms of integrating variable renewable energies such as wind and solar into the grid. This will control costs by cutting down emergency measures and assuring the least-cost energy procurement.

This line of work aims to determine predictive analysis methods for estimating consumption and production. These estimates serve as input to the optimization methods developed by Axis 1. The selected methods should be the most suitable among various engineering methods, including those based on modeling of the underlying physical

²The Industrial Agreement for Training through Research. This is an initiative of the French government to develop a relationship between academia and industries through funding arranged for doctoral research.

process. For example, stochastic methods, statistical methods, and artificial intelligence techniques (such as decision trees and forests, neural networks, support vector machines, regression, etc.).

The deployment of Linky³ meters and the increasing availability of external data sources, such as weather forecasts and demographic characteristics, offer ample opportunities to integrate additional inputs into the models. This enrichment enhances the accuracy of predictions. Moreover, advanced techniques like deep learning can be utilized, allowing the development of complex prediction models without relying solely on domain-specific knowledge.

The objective of this axis is to adapt or develop new predictive analysis techniques that meet the requirements of the optimization tool. This involves determining the most relevant methods and their inputs for each specific use case, considering variables to predict and the time horizon [Tri21], [ACT21].

The structure and management of the electricity network are expected to undergo changes due to the energy transition. Key factors contributing to this evolution include the significant and planned development of decentralized renewable energy-based production, electric mobility, storage assets, and digital transformation.

Axis 3 - Novel applications

With electrical energy demand anticipated to increase steeply for the coming future, partly because of the mass diffusion of electric vehicles and other electrification, the existing distribution networks must also be upgraded vastly seeing them not dimensioned for this purpose. Increasing electric vehicle integration will need very large charging infrastructure scales and further burden the grid. It would be followed by the need for investment and putting in place heavy grid upgrading. This includes upscaling capacities, advanced forecasting and management tools, besides integrating new technologies to ensure that effective supply-to-demand balancing is achieved. Without these essential adaptations, the stakes are raised for the stability of the grid, and there may even be reduced performance that compromises the reliability of the energy supply and the progress towards the sustainable goals on energy.

The objective of this axis is twofold: firstly, to study and identify the impact of deploying electric vehicles, storage, and microgrids on the SRD distribution network; and secondly, to assess the potential for centralized management of these assets by SRD, aiming to reduce initial investment costs and improve the quality of supply. To achieve this, Distribution System Operators (DSOs) need to develop methods that enhance distributed resources by integrating local flexibilities. These resources include stationary or mobile distributed storage with the Vehicle-to-Grid (V2G) concept, which can contribute to balancing and intelligently managing network voltage, modulating diffuse consumption, and managing distributed production. This approach takes into account the emergence of self-consumption and unitary or clustered micro-networks, with the primary objective of reducing or even avoiding the need for reinforcement investments or new infrastructure constructions.

³An advanced meter for electricity of the French utility company Enedis.

This axis is crucial for adapting and improving the optimization algorithm (in connection with axis 1) to incorporate different models and their integration, such as electric vehicles, storage, and microgrids, among others. By considering these additional parameters, the optimization algorithm can better reflect the complexity of the network and its optimization results. As a result, the IMAGE tool will be equipped to support investment decisions, enabling the Distribution System Operator (DSO) to identify the necessary and optimal investments for connecting new renewable assets.

Axis 4 - Industrialization of IMAGE

This axis involves the industrialization of IMAGE into a software tool, initially usable by SRD, and subsequently by other distribution network managers (DNOs). This tool will be designed to be modular, with software layers that facilitate its adaptability and scalability.

The industrialization of the IMAGE tool marks a crucial milestone in its path to market readiness. In this phase, the LabCom @LIENOR will establish a simulation environment for evaluating advanced functions, leveraging electrotechnical study software like Power Factory, ETAP, EMTP, etc. This environment enables the testing of functions developed across low TRL (Technology Readiness Level) axes and the validation of models and algorithms used. Subsequently, the focus shifts to developing interfaces and software solutions facilitating data routing for optimization calculations, generating and scheduling optimization problems, and accessing or editing data and calculation results through a secure user interface.

Following this phase, the @LIENOR LabCom will proceed to the SRD system integration stage, initiating the testing phase on the distribution network. This aspect will be overseen by the SRD smart grid engineer in conjunction with the dispatcher team to monitor integration stages and network operations. The LabCom @LIENOR team will analyze the results to validate the relevance and functionality of the IMAGE tool.

Objectives of the thesis

This thesis takes part in Labcom, in the axis 1. This axis, as we said, is the one that takes over the optimization, after taking the data as an input from the axis 2.

Previous work on this topic is presented in [Ali17], and this study aims to address and improve specific aspects of that work, particularly by upgrading the optimization model (IMAGE) in various ways. The primary objective is to devise methods for reducing computational time in solving the optimization problem. Additionally, additional constraints are incorporated to account for various electrical phenomena, including reactive power. Furthermore, the thesis introduces an innovative solution, such as power curtailment, to address the challenges posed by the increased integration of renewable energy sources and maintain the stability of the distribution network.

In the upcoming chapter, we will introduce the MIQP formulation, building upon the framework outlined in [Ali17] but incorporating enhancements in the formulation.

Subsequently, we will assess the contributions aimed at reducing computational time using the developed model. To evaluate the efficacy of these contributions, we will conduct tests using selected agencies from the SRD network and an academic electrical circuit. These tests will focus on assessing the capabilities of solvers such as Cplex and Gurobi in reducing computational time.

Chapter 3

The Distribution Network Reconfiguration problem

The *distribution network reconfiguration* (DNR) problem involves optimizing the network's configuration by adjusting its topology, which entails controlling switches and feeder connections. The primary objective is to enhance the efficiency and reliability of network operations, often targeting the reduction of power losses. The problem formulation of DNR typically leads to a non-linear formulation, specifically a Mixed Integer Non-linear Programming (MINLP) problem [Sil+21]. Traditional DNR methods approximate objective functions and constraints to first or second-order equations, resulting in formulations suitable for Mixed Integer Linear Programming (MILP) [TL18; GLG22] or Mixed Integer Quadratic Programming (MIQP) [TH12; JSP12]. This thesis focuses on an approximative DNR method based on MIQP which lies in the case of *exact methods* that are a way to solve the DNR problem.

3.1 The distribution network reconfiguration problem (DNR problem)

The Distribution Network Reconfiguration problem (DNR problem) is the way to reconfigure (change) the state (from ON to OFF or OFF to ON) of the switches in the distribution network. This reconfiguration differs from the first configuration (that is, the initial state of the switches) in the amount of power losses that is lower than the power losses of the first configuration. In fact, the DNR problem is a tool used to achieve the goal of minimizing the power losses in the distribution network.

The distribution network is represented by an underlying graph $G = (V, E)$ that is constructed basing on the GPS data of each electrical line, switch, load, generation, transformer etc. G maps each electrical component as a vertex or an edge. Each electrical branch is represented by an edge between two points with a dictionary of its characteristics (resistance, reactance etc.). Each switch is represented as an edge too if it is ON. In fact, a switch can connect two vertices or disconnect two vertices. The vertices of the graph are the set of loads, generations, sources (transformers HV/MV). Let $G = (V, E)$ be the underlying graph where V is the set of vertices (buses) and E the set of edges (Fig. 3.1).

A feasible configuration (solution) is a possible configuration of the state of switches that respects the different constraints required by the DSO. It represents a connected radial directed graph (Fig. 3.2).

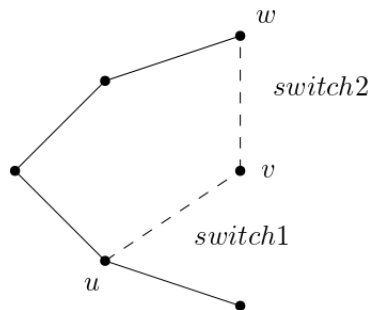


Figure 3.1: An underlying graph

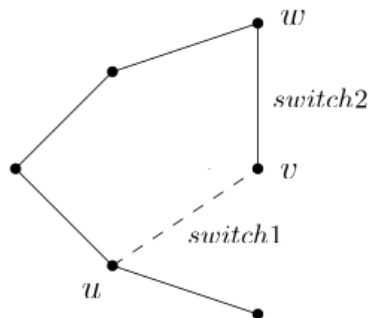


Figure 3.2: A feasible configuration

The reconfiguration problem presents enormous applications in real-work. Telecommunication networks can be reconfigured to improve the signal quality. Similarly to power systems, reconfiguration of routes for traffic management can reduce congestion, and optimize travel times in road and rail networks. Moreover, in supply chains, the logistics network configuration improves efficiency, reduces costs, and responds to changes in demand or supply disruptions.

As we will use the DNR problem as a way to reduce power losses in our context of power systems, the resolution is not evident due to the size of the distribution networks. In the next section, we will see how the feasible configurations can be enumerated in order to find the best one in function of the optimized quantity. Which is, the power losses in our context.

3.2 Resolution approach

The resolution of the DNR problem falls within the domain of operations research. A solution to the DNR problem would be to enumerate all the feasible configurations and calculate the amount of losses generated by each configuration. In the following subsection, we will see in general how configurations are obtained using an exhaustive way.

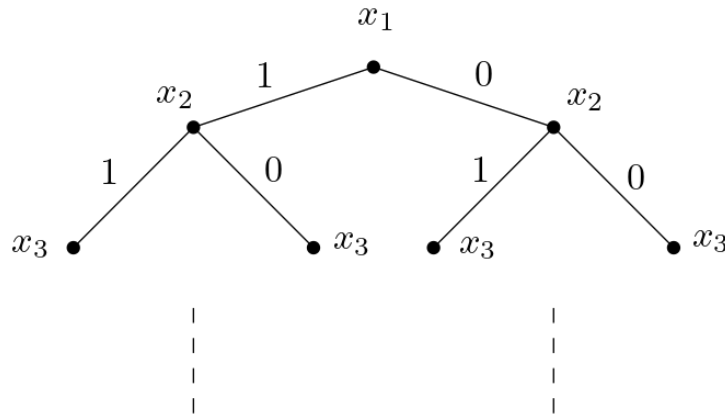


Figure 3.3: A decision tree

3.2.1 Exhaustive search of solutions

For networks where the number of decision variables is not high (< 50), the solution of the problem can be found by applying an algorithm that explores a decision tree by exhaustively listing all the possible solutions (Fig. 3.3). The decision for the Lth row whether it is ON/OFF is indicated by the binary decision variable:

$$x_L = \begin{cases} 1 & \text{if } Lth \text{ branch is ON} \\ 0 & \text{if } Lth \text{ branch is OFF} \end{cases}$$

So, for a total of K controllable branches, we will have 2^K possible configurations.

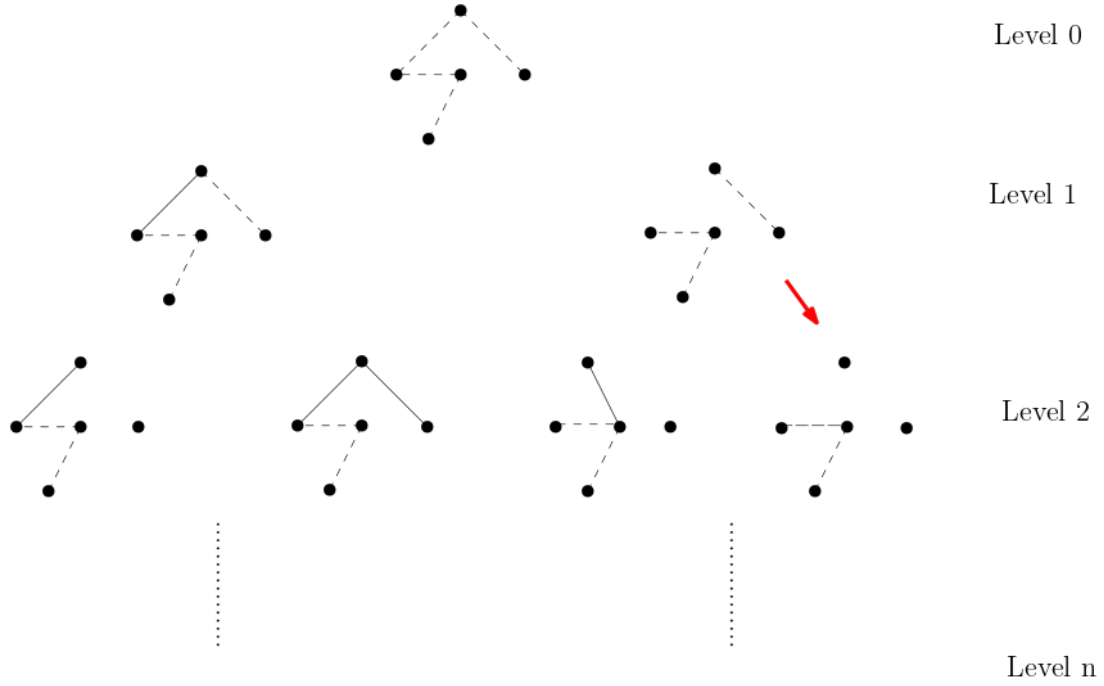


Figure 3.4: A decision tree

The Fig. 3.4, represents a decision tree for determining a radial topology with four controllable branches (dashed lines). At the beginning, (root vertex, level 0), all decision variables are undefined. Going down the levels, we affect a value to the different decision variables x_i . At the bottom of the decision tree (level n), each of the 2^k terminal vertices (leaves) is associated with a solution (which is not necessarily feasible).

By heading towards the leaves, it is obvious that we are not going to visit all of the leaves. Indeed, we can already prevent the tree of taking certain branches where we are certain that no feasible configuration exists. For example, in Fig. 3.4, when transiting from level 1 to level 2, we have four different configurations to examine. For configuration marked by a red arrow, the network is separated into two parts and this 'separation' of the network will be maintained for all configurations downstream of this branch of the decision tree. Thus, the constraint of radiality would no longer be satisfied.

3.2.2 Branch and Bound

Another decision to continue the search at a given branch can be made using a 'default rating'. It makes it possible to evaluate the value of a better theoretical solution following decisions already taken (we have assigned a value to the variables $x_0, \dots, x_i$). The solution is theoretical because we relax the binarity of the variables $x_0, \dots, x_i$. If a default assessment does not allow a feasible solution to be obtained, it is assigned a special value, for example $+\infty$. Thus, at a given level, we continue the search with the branch which gives the best evaluation. In operation research, this method is also known as *branch and bound* [Min08].

The Branch and Bound algorithm is widely used by solvers in order to reduce the size and the exploration time of the search space, as the exhaustive search conducts to search-

tree that grows exponentially with the number of binary variables. Consequently, a large-scale network becomes computationally untractable due to the number of combinations to explore. In contrast, the Branch and Bound technique prunes the search space to reduce computational time by solving a relaxed version of the problem to obtain an lower bound of the optimal solution. Then, based on the relaxed version, a tree-like search is created by branching on binary (decision) variables. Then, recursively, at each vertex of the tree, a lower bound on the optimal solution is found using a heuristic or a solution of a relaxation of the problem. Then, vertices with a lower bound worse than the current lower bound are not explored, which reduces the search space.

Conclusion

Given the very high number of possibilities (16698 switches, leading to over 16698 binary variables), it is almost impossible to carry out an exhaustive search of all the solutions. However, listing a certain number of them according to certain criteria linked to knowledge of the studied network could be considered.

The second approach could be to calculate the load distribution which minimizes the losses in the fully meshed network without worrying about the radial configuration. This problem is also called *Optimal Power Flow* (OPF) [DT68]. Then from the result of this distribution load, we can try to determine which switches must be manipulated to obtain these flows in the network.

The inconvenient of these approaches is both to find the best solution while doing an exhaustive search for all configurations, or in the non-linearity of the power flow equations (see Section 1.6). In fact, the reconfiguration is a combinatoiral problem [CRP08] that deals with discrete objects (state of switches) and finding the best combination that satisfy the minimum power losses (as a criterion for example).

While the problem of reconfiguration of the network is claimed by most DNR-related papers since the 1970's (e.g. [Hel+21]), a proof of its NP-hardness, based on a reduction of 3-Partition, is given in [Kho+18]. The different techniques used for its resolution are shared between heuristics, meta-heuristics and methods so-called exact optimizations. We will briefly present them in the following section.

3.3 State of the art

In the world of optimization problems, in particular in the context of DNR, various approaches have been developed and refined. Heuristics and metaheuristics stand as prominent methodologies, each with its distinct characteristics and applications.

3.3.1 Heuristic methods

In [Kho+09], a heuristic is based on the optimal power flow simulation. The optimal power flow will give a solution that is meshed and without radiality constraints. The optimal power flow is applied to an optimization problem with binary variables and an objective function to minimize power losses. Then, slackness variables are introduced into constraints that guide the research of the optimal configuration. The process finishes when these slackness variables are null. In [AM15], a heuristic to solve the optimization problem is presented. It is based on the research of a minimum spanning tree (a *spanning tree* is a subgraph of a graph that is a tree and connects all the vertices of the original graph). The procedure is based on an optimal power flow simulation, and then obtain the radiality by attributing current's value for each branch, and the algorithm is guided to a radial solution that is close to the value of the power losses given by the optimal power flow. In [Cav17], a heuristic finds a reconfiguration using the approach of maximum flow with minimum cost in the graph. The max flow min cost finds the maximum quantity of flow (which is active power in our case) from a source to a sink (load points) with minimizing the cost of sending this flow (sum of power losses). The disadvantage of this method is that the solution is not guaranteed as optimal, which is evident. In [Sch+05], the optimization problem is modeled as a non-linear problem with mixed integer variables. The binary variables correspond to the state of switches. The resolution is done by starting with a meshed network, and iteratively branches to generate the least power flow (load flow) simulation. In [Gom+05], the algorithm uses a heuristic procedure that starts with the system in a meshed topology, with all controllable switches closed. The choice of the switches to be opened is based on the calculation of the minimum total system losses, using a load-flow program. In [HD23], they propose a two-stage heuristic method focusing on computational efficiency and reliability in radial DNR. In [Bar+21], an heuristic that explores Sequential Switch Opening (SSO) and genetic algorithms for efficient DNR in a practical scenario. In [Guo+22], it provides insights into various heuristic techniques and their applicability in loss reduction and reliability improvement. In [RKB22], it introduces hybrid approaches combining heuristics and genetic algorithms for optimal network configurations. In [HH23], a heuristic that combines learning patterns for enhanced topology optimization and operational efficiency in power distribution. In [Zar+24], a heuristic that employs cooperative techniques in order to address renewable energy integration and loss minimization. In [Jia+24], a heuristic for the dynamic the case of dynamic reconfigurations is discussed. In [Zhe+23], a heuristic with data-driven techniques is integrated for faster and reliable reconfiguration. In [MK22], it analyzes heuristic-inspired metaheuristic approaches like Ant colony for better resource allocation and configuration.

We therefore see that heuristics can be used at different steps of the problem. They can simplify the search for a configuration either by relaxing the binary part of the problem

or by facilitating the computational of load's distribution using a specific algorithm.

3.3.2 Metaheuristic methods

Metaheuristic methods are strategies to solve optimization problems that do not need an optimal solution but want to efficiently examine the solution space to find acceptable solutions. In the context of the Distribution Network Reconfiguration (DNR) problem, many metaheuristic methods have been applied to find near-optimal solutions. In this section, we will provide some common metaheuristic for the DNR problem. In 1992, the genetic algorithm was introduced for the first time in [Nar+92]. In [Rao+10], a metaheuristic for the DNR problem with the objective of minimization of power losses is employed using the *harmony search*. The harmony search was first introduced in [GKL01] and it consists of choosing many points as potential solutions (named as harmonies) and an algorithm that iteratively refines the harmonies (see [GKL01]). The advantages of this method is free from power flow simulations, and it focuses on the search of the configuration by keeping in mind the branches that make a cycle. In [ZFZ07], a metaheuristic using *tabu search* algorithm is used. It was first introduced in [Glo86]. The concept of this algorithm is to search for a solution around or near candidate solution or an initial solution. In [Mah+21a], a review that analyzes various metaheuristic techniques and compare them to a novel approach based on efficient genetic algorithm. In [Bar+21], a comparative study that focuses on genetic algorithms and the heuristic of Sequential Switch Opening (SSO) to enhance the DNR. In [BCW24], a procedure that solves the DNR problem under uncertainty and determines the optimal topology using a deep neural network architecture. In [Raz+22], in the context of improving the daily performance of an active distribution network, a multiobjective optimization is applied to a DNR including a metaheuristic that finds an optimal scenario among a set of scenarios that is determined using a stochastic approach.

The inconvenient of this type of methods is the lack of proof of the optimality of the solution. Moreover, their algorithm could take too much time, because of the large number of iterations to converge to an acceptable solution.

3.3.3 Machine learning methods

As a field of artificial intelligence, *machine learning* methods focus on algorithms that let the computers make decisions based on archived data without being implemented. As an example for these methods is the *artificial neural network* (ANN), which is inspired from the structure of the human brain [Abi+19]. It consists of interconnected vertices via links, that are called neurons, each one has a weight and receives input signals, processes them and passes the output to other neurons. The output of each vertex is obtained by applying specific non-linear function on the sum of its input. The weights are calculated via a training algorithm and they are the result required to solve a problem. ANN are capable of learning complex relationships in data and other complex practices.

The feature of ANNs in the context of DNR problem is the capability to provide real-time optimal topologies without executing extensive iterative procedures [SGR06]. The DNR problem based on ANNS takes as input the active and reactive power demands and

the output is an optimised topology [Kas+98]. In [Fat16], a tree designing the ANN tends to reduce power losses where loads are classified into clusters to reduce the size of the ANN.

3.3.4 Exact methods

Exact methods, or deterministic methods, are algorithms that tends to find the optimal global solution to an optimization problem with a finite amount of time. In fact, despite of the fact that the DNR problem is NP-hard (takes exponential time to find the optimal in the worst case), exact methods can still be used to solve the DNR problem efficiently.

The main reason for this is that the problem size can be manageable by the solver in a way that it can decompose the problem into subproblems and can find an optimal or near-optimal solution. Moreover, advances in computational hardware and software have increased the computational power available to solve optimization problems. For example, in the branch and bound exact method, the size of tree-search is exponential with its size. So, with the intense capabilities of the hardwares in exploring the search space, and with the some heuristics in searching, the computation of the optimal solution becomes available.

In [MB75], the DNR problem was proposed by Merlin for the first time as an approach to reduce power losses. He used a branch and bound method with a DC load flow to solve the reconfiguration problem. In [SH89], an optimal flow pattern for loss reduction is developed. In [GLG22], a MILP is used to solve reconfigurations and capacitor optimal placement. In [Zha+18], a Mixed Integer Quadratically Constrained Quadratic Programming (MIQCQP) is presented for a DNR with loss reduction and solved using the CPLEX solver.

In addition, the objectives of the DNR problem can vary [Mah+21b]. In fact, decreasing power losses has been the main objective of the reconfiguration problem. Some other objectives have been considered for DNRs [RRR10], [TH12], [Bor12], [Rao+12], [HT15]. Reconfiguration can be with the goal of improving the voltage profiles by changing the flow of active and reactive power in a distribution network [Otu+23]. DNR can improve the ability the system under planned conditions as defined with reliability [Sul+16]. The reliability indices can be improved by changing the flow of active and reactive power that affect the current magnitude of branches [Ant+21]. Moreover, reconfiguration can improve the harmonic losses (where the current and voltage are deviated from the sinusoidal waveforms) of the distribution network [AJB19], [RJ23]. Also, reconfiguration can improve the voltage unbalance and related power losses by changing the phase loads in a three-phase distribution network [Sal21], [GCS22]. The literature also presents studies on decreasing the operational cost such as the demand response participation [LS23], operational cost of microgrids [KFS20], [KBS22], power losses [Esm+19] and switching cost [LJD16] using the DNR. Moreover, the capability of the reconfiguration to increase the distributed generation hosting capacity has been improved [Dia+20], [AAE22], [ČJ20].

On the other side, for heuristics, these techniques require a good knowledge of the particularities of the problem to optimize. This makes the method specific to a particular

type of problem. but has the advantage of being generally efficient because it exploits the specific characteristics to the target problem.

However, heuristics and meta-heuristics are usually fast, but the disadvantage is that the optimality of the solution is not proved.

For that reason, the exact optimization methods are used to solve the DNR problem in this thesis. In the next section, the Mixed Integer Quadratic Programming (MIQP) used in this thesis is presented.

3.4 Model description

3.4.1 General statement

A distribution network typically operates with a forest topology¹ due to the simplicity of designing protection devices for this configuration. However, loops are possible, although they are usually left open (i.e., loop operation remains open). This approach is primarily justified by the necessity to restore power to areas affected by outages, such as those caused by short circuits on a line.

Under normal operating conditions, the open switch in the loop does not face any specific constraints as long as the lines are not overloaded and the nodal voltages remain within specified limits. Often, this open switch is selected according to certain optimization criteria, such as minimizing power losses. In some distribution networks where the number of loops is small and the loops are independent of each other (i.e., not adjacent), the number of possible combinations for opening branches is limited. By evaluating all potential cases, it is relatively straightforward to identify the optimal opening points.

However, when loops are no longer independent² the number of possibilities increases exponentially.

3.4.2 Representation of the distribution network

The distribution network is represented as a non-oriented graph $G = (N, E)$ where N is the set of vertices and E is the set of edges. Each branch (electrical line, switch) is represented by a single edge. Each vertex represent a load, producer or a vertex that has no load or producer.

G is the input of the MIQP models that will be detailed in the next sections. In other words, the following constraints and objective function are applied to G

- **Objective function:** *Minimize* power losses (Joules losses)
- **Constraints:**
 - *Radiality* of the topology
 - *Fictitious flow*: Constraints to prevents loops that can be created because of generations feeding consumers independently from the transformer HV/MV. This is called islanding
 - *Power balance constraint*: The conservation of active and reactive power in the network

¹a tree for each source, because two sources can not be connected

²which is typically the case for our target industrial work

- *Voltage limits*: The control of voltage on each vertex in the graph
- *Branch limits*: Restriction of the apparent power within each branch
- *Source limits*: Limitation of the apparent power within the sources

3.4.3 Optimization criteria

The optimization criterion in the model is *minimizing power losses*. These losses are associated with the characteristics of the distribution lines through which power is transmitted. A line is typically represented using a *pi-model* (Fig. 3.5), where the line is expressed as a series combination of resistance (R) and reactance (X). These two components are derived from the impedance formula $z = R + i \cdot X$, which is a complex number representing the relationship between R and X for a given line. The reactance (X), measured in ohms (Ω), represents the opposition to current flow caused by capacitive or inductive effects, resulting in the exchange of reactive power between the source and the load. The *capacitance* (C), measured in farads per meter (F/m), contributes to the system's reactive power requirements, which helps maintain voltage regulation.

In the presented model, capacitance is neglected due to its relatively small magnitude compared to resistance and reactance.

For an edge (u, v) , the power losses through it is $Z = R(u, v) \cdot I(u, v)^2$. While $I(u, v) = \frac{S(u, v)}{U_N}$. Here, the voltage of each vertex of the network is approximated at its given nominal value U_N . This approximation is only applied to the computation of the objective function. Thus, we will have the amount of power loss of a single branch (u, v) : $Z = \frac{1}{U_N^2} \cdot R(u, v) \cdot S(u, v)^2$ and the goal is to *minimize* the sum of all power losses of all branches. In other words:

$$\min Z = \frac{1}{U_N^2} \sum_{(u, v) \in E} R(u, v) \cdot S(u, v)^2 \quad (3.1)$$

3.4.4 Radiality constraints

As mentioned earlier, the radial structure of the operating scheme is critical. A radial configuration requires fewer protective devices compared to a meshed one and facilitates more effective voltage regulation, particularly from the substations.

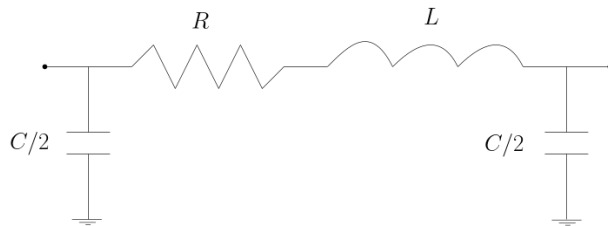


Figure 3.5: A line as a pi-model

Furthermore, the significance of radiality becomes apparent in the context of decentralized producers, such as renewable energy sources. Radial networks offer enhanced resilience, crucial for isolating faults and ensuring voltage regulation, especially in the face of increased integration of renewable energy sources. Additionally, the flexible nature of radial networks allows for easy accommodation of decentralized producers without requiring extensive upgrades or modifications to the network.

In the next sections, we distinguish two MIQP models that will be used in the contributions. The difference between the two models lies in the representation of the radiality constraints. The first one is a MIQP with bidirectional binary variables. There are many ways to impose the radiality of the operating scheme. In our work, we have used two different way to impose radiality of the feasible configuration.

3.5 A MIQP with bidirectional binary variables

As discussed in the preceding section, the network is modeled as a graph $G = (N, E)$. For a vertex u , let $N(u)$ be the set of neighbors of u . In the MIQP with bidirectional binary variables, each edge (u, v) is represented by two binary variables $b(u, v), b(v, u) \in \{0, 1\}$. In other words, each edge is split into two binary variables (see Fig. 3.6), and we must impose the constraints that at least one of them is null. Otherwise, both will be equal to 1 and we will have a cycle between u and v . Now, in order to ensure that the solution does not contain a cycle (which is necessary to obtain a radial topology), we must require two conditions:

- For each non-source vertex, there must be one and only one vertex conducting to it among all its neighbors (see Fig. 3.7).
- For each source vertex, it must not be conducted (mapped) by any another vertex.

By imposing those conditions, we guarantee that we have a radial graph. Since each non-source vertex will be normally connected to a unique source vertex. Mathematically, the following constraints are imposed. Moreover, the following constraints are used in [Ali17], [Ali+16] where they are briefly described.

Constraints that impose radiality

We consider that in normal operations, the source is injecting power in the network.

- $\sum_{v \in N(u)} b(v, u) = 0$, for each source vertex u
- $\sum_{v \in N(u)} b(v, u) = 1$, for each non-source vertex u

Additional constraints are used for each *controllable* and *non-controllable* branch. A *controllable* branch is a branch that contains a switch. A *non-controllable* branch is a

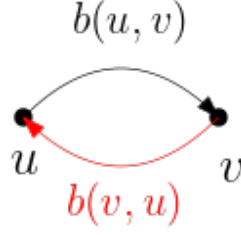


Figure 3.6: An edge (u, v) splitted into two binary variables

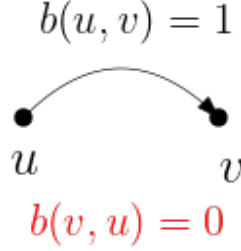


Figure 3.7: A vertex v must be conducted by one and only vertex

branch that does not contain a switch. The following constraints guarantee the circulation of current in one way between any two branch (u, v) . Additionally, if the branch is non-controllable, then one of $b(u, v)$ or $b(v, u)$ takes its initial state (ON/OFF) which is represented by the variable $init(u, v)$. Otherwise, in the second constraint, $b(u, v)$ and $b(v, u)$ can be both null or at most one of them take the value 1 for any controllable branch. This allows controllable branches to change their state (ON/OFF) depending on the choice of the solver.

- $b(u, v) + b(v, u) = init(u, v)$, for any non-controllable branch (u, v)
- $b(u, v) + b(v, u) \leq 1$, for any controllable branch (u, v)

In Fig. 3.8, DG represents a distributed generation (producer), while u , v , and $load$ denote loads. Both $switch1$ and $switch2$ are switches that can be either ON or OFF. The $source$ vertex represents a substation.

Let's suppose that DG can supply energy to satisfy u and v . For instance, if DG produces 10 MW (MegaWatts) of energy and both u and v consume 5 MW each, a feasible solution can be achieved while meeting the radiality constraints outlined in this subsection.

As we can see in Fig. 3.9, the $switch1$ can be opened (state: OFF), while $switch2$ is closed, isolating u , v and DG . Each non-source vertex $\{u, v, DG, load\}$, verifies the first constraint. Typically, we have for all $u \in \{u, v, DG, load\}$, $\sum_{v \in N(u)} b(v, u) = 1$. Moreover, for the source vertex $source$, we have effectively: $\sum_{v \in N(u)} b(v, source) = 0$. In particular,

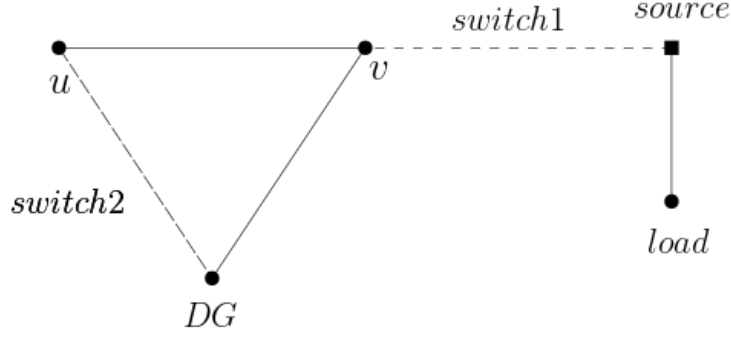


Figure 3.8: The underlying graph

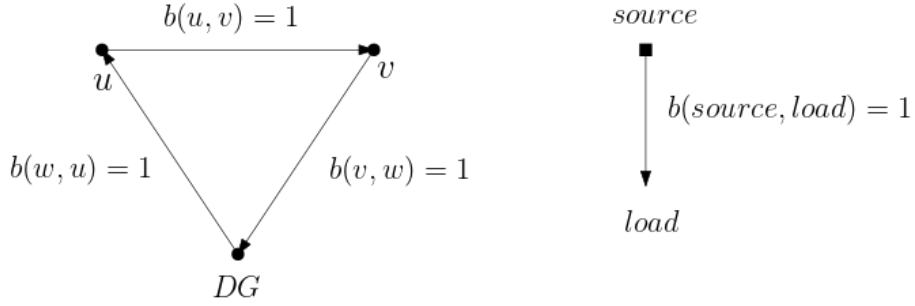


Figure 3.9: A feasible solution

$b(load, source) + b(v, source) = 0$. So, the second constraint is verified for all source vertices.

Consequently, the constraints in 3.5 are not sufficient to obtain radially. In Fig. 3.9, we have a feasible solution that is not radial while respecting the studied constraints. Thus, we must introduce additional constraints that prevent from feasible solutions that contain cycles especially in the case of the presence of distributed generations.

In our work, we have found a solution for this problem. The procedure is presented in details in [Lav+11]. It consists in introducing a *fictitious flow* as additional constraints to obtain a feasible solution as we want.

3.5.1 Fictitious flow

The *fictitious flow* is introduced for each vertex in the graph. Its behavior is like the behavior of power respecting the law of conservation of power in the network, that derives from Kirchhoff's law as we will see in the coming sections. It imposes to the feasible solutions the connection of each non-source vertex of the underlying graph to be connected to a source by supposing that each of those vertices is a consumer of the fictitious flow while the source vertices inject the fictitious power in the network. The intention behind it is that each producer vertex must be connected to the source. By [Lav+11], ensuring the radially of a solution requires two conditions:

- For a graph $G = (V, E)$ where $|V|$ is the number of vertices and $|E|$ the number of edges, we have: $|V| = |E| + 1$
- G must be a connected graph, i.e, if we consider the underlying non oriented graph, there is a path between each vertex.

In fact, a tree-graph G satisfies the first condition. Nevertheless, in case of partitions in the graph (see Fig. 3.9) we have for example: $|V| = 5, |E| = 4$. So, $|V| = |E| + 1$ is ensured, but the underlying non oriented graph is not connected.

In case of disconnections in the graph, a distributed generation supplying some loads independently from the source. So, a cycle will definitely appears, because if it is not the case, the distributed generation would be linked to a source by a path. Thus, the second condition is violated. [Lav+11] proposes the following constraints to ensure the connection of all distributed generations to a source.

3.5.2 Constraints of fictitious flow

The fictitious flow is an imaginary flow where the concept is that all non-source vertices are consumers and the source vertices inject the fictitious flow in the network. Therefore, all non-source vertices must be connected to a source vertex, which will prevent the case of creation of islanding in the feasible configuration.

For each non-source vertex u :

$$\sum_{v \in N(u)} f(v, u) - f(u, v) = \mathbf{f}_{eq}(u) \quad (3.2)$$

For each source vertex u :

$$yfs(u) + \sum_{v \in N(u)} f(v, u) - f(u, v) = \mathbf{f}_{eq}(u) \quad (3.3)$$

$yfs(u)$ is a variable representing the fictitious power injected at source u . The variable $f(u, v)$ is the fictitious power in the edge (u, v) and $\mathbf{f}_{eq}(u)$ is a data representing the quantity of the fictitious power spent at vertex u and can be as a data for the optimization as follows. Note that $P_{eq}(u)$ is the equivalent power at vertex u . If $P_{eq}(u) < 0$, then u is a producer. Otherwise, it is a load:

1. For each vertex u , we initialize $\mathbf{f}_{eq}(u)$ as 0
2. If $P_{eq}(u) < 0$ or u is a non-injection vertex ($P_{eq}(u) = 0$), $\mathbf{f}_{eq}(u) = 1$

The following constraint takes into account the relation between the state of each edge and the value of the fictitious power flowing through it. For each branch (u, v) . It imposes

that the value of the variable $f(u, v)$ by the value of the data $\mathbf{f}_{max}$ if the binary variable $b(u, v)$ equals 1. Otherwise, it equals 0:

$$-\mathbf{f}_{max} \cdot b(u, v) \leq f(u, v) \leq \mathbf{f}_{max} \cdot b(u, v) \quad (3.4)$$

Where f_{max} is the maximum fictitious power, and it is computed (before the optimization) as follows:

$$f_{max} = \sum_{\forall u \in N} \mathbf{f}_{eq}(u) \quad (3.5)$$

Thus, for an edge (u, v) , if $b(u, v) = 1$ then $b(v, u) = 0$, we will have $f(u, v) = 1$ and $f(v, u) = 0$.

Now, we will see how those constraints exclude the non-acceptable solutions. In other words, the solutions that are not radial but verify the radially constraints in 3.5. Let's see the network in Fig. 3.8: a graph G representing a network with a given state of the switches. We will apply the fictitious constraints on G without consideration of the state of switches, and see how these constraints prevent from obtaining a cycle.

In fact, applying the radially constraints on this graph can lead to the non-radial solution (given in Fig. 3.9). Now, by applying the fictitious flow on G , for each vertex in G , we have:

- For vertex *source*: $yfs(source) = f(source, load) - f(load, source) + f(source, v) - f(v, source)$
- For vertex *load*: $f(source, load) - f(load, source) = \mathbf{f}_{eq}(load)$
- For vertex v : $f(source, v) - f(v, source) + f(u, v) - f(v, u) + f(DG, v) - f(v, DG) = \mathbf{f}_{eq}(v)$
- For vertex u : $f(v, u) - f(u, v) + f(DG, u) - f(u, DG) = \mathbf{f}_{eq}(u)$
- For vertex DG : $f(u, DG) - f(DG, u) + f(v, DG) - f(DG, v) = \mathbf{f}_{eq}(DG)$

Moreover, we have the constraints that determine the relation between $f(u, v)/f(v, u)$ and $b(u, v)/b(v, u)$ for each edge (u, v) .

Now, we will replace each variable by its value in case that the solver chooses the Fig. 3.9 as a solution. We will have that $f(v, u) = f(DG, v) = f(u, DG) = f(load, source) = f(v, source) = f(source, v) = 0$, due to the fact that $b(v, u) = b(DG, v) = b(u, DG) = b(load, source) = b(source, v) = b(v, source) = 0$.

Moreover, the variables $f_{eq}(u) \forall u \in G$ are data calculated before applying the constraints. Here, for example, we have $f_{eq}(DG) = 1$ and $f_{eq}(u) = 0$ for all the remaining vertices. We will have:

- For vertex *source* : $yfs(source) = f(source, load)$
- For vertex *load* : $f(source, load) = 0$
- For vertex *v* : $f(u, v) = f(v, DG)$
- For vertex *u*, $f(DG, u) = f(u, v)$
- For vertex *DG*, $f(v, DG) = f(DG, u) + 1$

Therefore, we will have $f(v, DG) = f(DG, u) + 1 = f(u, v) + 1 = f(u, v)$. Thus, a contradiction. Therefore, the Fig. 3.9 is not a possible solution. Thus, the solver, by applying the fictitious constraints, will be able to filtrate this solution.

3.5.3 Power balance constraints

The power flow must obey to the first law of Kirchhoff on vertices. On each vertex *u*, the sum of all input flows at a vertex must be equal to the flows exiting from the vertex. We call this law as *law of vertices* too. These power balance constraints assume no power losses at each vertex, which simplifies the DNR problem into an approximate one where losses are not included in the incoming and outgoing power.

For each non-source vertex *u*:

$$\sum_{v \in N(u)} yp(v, u) - yp(u, v) = \mathbf{P}_{eq}(\mathbf{u}) \quad (3.6)$$

$$\sum_{v \in N(u)} yq(v, u) - yq(u, v) = \mathbf{Q}_{eq}(\mathbf{u}) \quad (3.7)$$

For each source vertex *u*:

$$yps(u, t) + \sum_{v \in N(u)} yp(v, u) - yp(u, v) = 0 \quad (3.8)$$

$$yqs(u, t) + \sum_{v \in N(u)} yq(v, u) - yq(u, v) = 0 \quad (3.9)$$

For each source vertex *u*:

$$\mathbf{P}_{eq}(\mathbf{u}) = Pload(u) - Pdg(u) \quad (3.10)$$

$$\mathbf{Q}_{eq}(\mathbf{u}) = Qload(u) - Qdg(u) \quad (3.11)$$

- $yp(u, v)$: the active power flow through the edge (u, v)

- $yq(u, v)$: the reactive power flow through the edge (u, v)
- $yps(u)$: the active power flow at the source u
- $yqs(u)$: the reactive power flow at the source u
- $Pload(u)/Pdg(u)$: The amount of consumed/produced active power at u
- $Qload(u)/Qdg(u)$: The amount of consumed/produced reactive power at u

In this formulation, we can take in account the distributed generations (renewable energy). At a vertex u , if this vertex is a generation, then $P_{eq}(u) < 0$. Therefore, the variable at each edge $yp(u, v)$ will take negative values. The flow variable yp/yq can take positive or negative values depending on P_{eq}/Q_{eq} .

It is worth to say that the variables yp/yq depend on the chosen feasible configuration. In other words, it depends from the binary variables that correspond the state of each edge. In the next sections, we will put in evidence the relation between binary and continuous variables.

3.5.4 Voltage variation limits

The goal of these constraints is to control the voltage at each vertex. The following constraints are extracted from [BW89], [Ram+05] that modelize the physical equation of voltage drop between two neighbors in the graph. Those constraints are the result after the approximation of the drop voltage between two vertices u and v . For two neighbor vertices u and v , the physical equation of the drop voltage is $V_u = V_v + \Delta V$ and $\Delta V = Z_{uv} \cdot I$ is the drop voltage between u and v . Z_{uv} is the impedance of the line between u and v . After expressing this formula as complex numbers, V_u is computed in terms of its real and imaginary part: $V_u^2 = Re(V_u)^2 + Im(V_u)^2$. $Re(V_u)^2$ is the real part of V_u and $Im(V_u)^2$ is its imaginary part. Therefore, in the constraints, the variable Us is a linear variable representing the squared voltage by taking the squared of the range of drop and elevation voltage as its domain.

For each non-source vertex u :

$$Us(u) = \sum_{v \in N(u)} yUs(v, u) - 2 \cdot (\mathbf{R}(\mathbf{u}, \mathbf{v}) \cdot yp(v, u) + \mathbf{X}(\mathbf{u}, \mathbf{v}) \cdot yq(v, u)) \quad (3.12)$$

$X(u, v)$ is a data representing the reactance of the branch (u, v) . $Us(u)$ is a variable representing the squared voltage at vertex u . We remind that each edge in this model is represented by two binary variables $b(u, v)$ and $b(v, u)$. $yUs(u, v)/yUs(v, u)$ is an intermediate variable that equals $Us(u)$ or null, based on the value of the binary variable

$b(u, v)/b(v, u)$. The following constraints establish the relation between $yUs(u, v)$ and $b(u, v)$.

For each $(u, v) \in E$:

$$\mathbf{Us}_{min} \cdot b(u, v) \leq yUs(u, v) \leq \mathbf{Us}_{max} \cdot b(u, v) \quad (3.13)$$

$$\mathbf{Us}_{min} \cdot (1 - b(u, v)) \leq Us(u) - yUs(u, v) \leq \mathbf{Us}_{max} \cdot (1 - b(u, v)) \quad (3.14)$$

From (3.13), if $b(u, v) = 0$ then $0 \leq yUs(u, v) \leq 0$ and we will have $yUs(u, v) = 0$.

Otherwise, $Us_{min} \leq yUs(u, v) \leq Us_{max}$ where $Us_{min} = 0.95^2 \cdot U_N^2$ and $Us_{max} = 1.05^2 \cdot U_N^2$. In fact, SRD (DSO of the distribution network in Vienne in France) imposes a limit of 5% of U_N of reduction or elevation of voltage on each voltage vertex taken in the network.

From (3.14), if $b(u, v) = 1$, we will have $0 \leq Us(u) - yUs(u, v) \leq 0$. Thus, $Us(u) - yUs(u, v) = 0$ and then $yUs(u, v) = Us(u)$. Therefore, the drop voltage at node u is:

$$Us(v) = Us(u) - 2 \cdot (\mathbf{R}(\mathbf{u}, \mathbf{v}) \cdot yp(u, v) + \mathbf{X}(\mathbf{u}, \mathbf{v}) \cdot yq(u, v)) \quad (3.15)$$

One more constraint is required, it is to fix the voltage at the source (substation) vertex as the square of the wanted nominal voltage U_N .

For each source vertex u :

$$Us(u) = \mathbf{U}_N^2 \quad (3.16)$$

Regarding those constraints, we can see that for each branch (line, switch), we have two intermediate variables ($yUs(u, v)/yUs(v, u)$).

3.5.5 Branch limits

This section is devoted to establish the relation between the active/reactive flow variables in each edge and the binary variables corresponding to those edges.

To limit the apparent power within each branch, the following constraints are enforced, assuring that the flow in an edge (u, v) is zero if the binary variable associated with this edge is set to zero. Otherwise it equals $Smax(u, v)$ which is the maximal apparent power of (u, v) that depends on physical characteristics of the line (length, section, material or etc.).

For each edge $(u, v) \in E$:

$$\begin{aligned} -\mathbf{Smax}(\mathbf{u}, \mathbf{v}) \cdot b(u, v) &\leq yp(u, v) \\ &\leq b(u, v) \cdot \mathbf{Smax}(\mathbf{u}, \mathbf{v}) \end{aligned} \quad (3.17)$$

$$\begin{aligned}
-\mathbf{Smax}(u, v) \cdot b(u, v) &\leq yq(u, v) \\
&\leq b(u, v) \cdot \mathbf{Smax}(u, v)
\end{aligned} \tag{3.18}$$

$$\begin{aligned}
-\sqrt{2} \cdot \mathbf{Smax}(u, v) \cdot b(u, v) &\leq yp(u, v) + yq(u, v) \\
&\leq \sqrt{2} \cdot \mathbf{Smax}(u, v) \cdot b(u, v)
\end{aligned} \tag{3.19}$$

$$\begin{aligned}
-\sqrt{2} \cdot \mathbf{Smax}(u, v) \cdot b(u, v) &\leq yp(u, v) - yq(u, v) \\
&\leq \sqrt{2} \cdot \mathbf{Smax}(u, v) \cdot b(u, v)
\end{aligned} \tag{3.20}$$

So, for each branch from u to v , the power variables $yp(u, v)/yp(v, u)$ will depend directly on the state of the binary variables (same for $yq(u, v)/yq(v, u)$).

As we know, we have $S^2 = P^2 + Q^2$. So, the constraints (3.17), (3.18), (3.19) and (3.20) are an approximation of the previous equation. In fact, to limit the active and reactive power through an edge (u, v) , then we must have $yp(u, v)^2 + yq(u, v)^2 \leq S_{max}(u, v)^2$. In other words, on the (yp, yq) plane, the real limitation is the circle with center $(0, 0)$ and a radius $S_{max}(u, v)$. This circle has been approximated by the a octagon limited by the red, blue and dark red lines due to the non-linearity of the equation $yp(u, v)^2 + yq(u, v)^2 \leq S_{max}(u, v)^2$ (the variables are not linear).

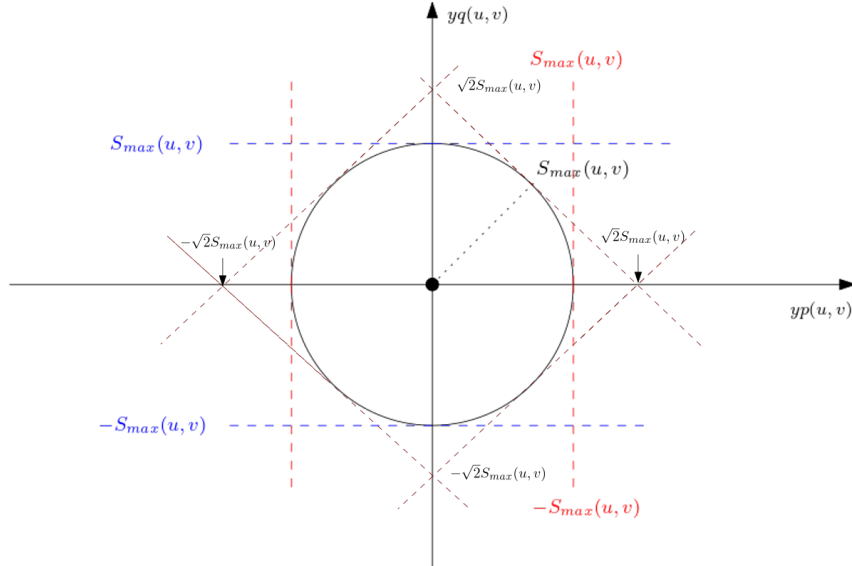


Figure 3.10: The approximation of $yp(u, v)^2 + yq(u, v)^2 = S_{max}(u, v)^2$ for an edge (u, v)

As we can see in Fig. 3.10, the domain of $yp(u, v)^2 + yq(u, v)^2 \leq S_{max}(u, v)^2$ is the disk. After approximation, the domain becomes limited by the lines in red and blue.

3.5.6 Source limits

To limit the apparent power flowing through the source, the following constraints are added:

For each source vertex u :

$$\begin{aligned} -\mathbf{Smax}(u) &\leq yps(u) \\ &\leq \mathbf{Smax}(u) \end{aligned} \quad (3.21)$$

$$\begin{aligned} -\mathbf{Smax}(u) &\leq yqs(u) \\ &\leq \mathbf{Smax}(u) \end{aligned} \quad (3.22)$$

$$\begin{aligned} -\sqrt{2} \cdot \mathbf{Smax}(u) &\leq yps(u) + yqs(u) \\ &\leq \sqrt{2} \cdot \mathbf{Smax}(u) \end{aligned} \quad (3.23)$$

$$\begin{aligned} -\sqrt{2} \cdot \mathbf{Smax}(u) &\leq yps(u) - yqs(u) \\ &\leq \sqrt{2} \cdot \mathbf{Smax}(u) \end{aligned} \quad (3.24)$$

Where $yps(u) \setminus yqs(u)$ is the active \reactive power injected(+)/absorbed(-) at source u . $\mathbf{Smax}(u)$ is the maximum apparent power at the source u .

In fact, the apparent power limit at a source u is determined by the equation $yps(u)^2 + yqs(u)^2 \leq S_{max}(u)^2$. Thus, due to the non-linearity of this constraint, the constraint (3.21), (3.22), (3.23) and (3.24) are an approximation of the real constraint (same as the previous section).

3.6 A MIQP with one binary variable per edge

The MIQP with one binary variable per edge presents another way to impose the radiality constraints than the previous section. The advantage of this MIQP is that we have a less number of binary and continuous variables (the half) than the MIQP with bidirectional binary variables. In fact, in the MIQP with bidirectional binary variables per edge, each edge is represented by two binary variables. Then, for each binary variable, $b(u, v)$ and $b(v, u)$ for an edge (u, v) , we have a continuous variable for the active power $yp(u, v)$ and $yp(v, u)$. In contrast, in the MIQP with one binary variable per edge, each edge (u, v) is represented by one binary variable $d(u, v)$ and the active power flow is represented by only the variable $yp(u, v)$. Since the direction of the active power flow is determined by the sign of the variable yp in both MIQP models, the representation of each edge with two binary variables becomes less interesting than its representation with only one binary variable in terms of the size of the search space. Therefore, it becomes interesting to apply the MIQP with one binary variable per edge where we have a less number of total variables. On the other hand, a new formulation for voltage variation constraints is applied.

The underlying graph in input for the MIQP with one binary variable per edge is an oriented graph $G = (N, A)$. Each arc is represented by the binary variable $d(u, v)$.

Let E_{SW} be the set of edges that have a switch, $N_{src} \subset N$ be the set of source vertices, $N_{non-src} \subset N$ be the set of non-source vertices, $N_{DG} \subset N$ be the set of DG vertices and $N_{zi} \subset N$ be the set of zero injection vertices. For a vertex u , $N^{in}(u) \subset N$ is the set of direct predecessors of u and $N^{out}(u) \subset N$ the set of direct successors of u .

3.6.1 Radiality constraints

The feasible solution needs to be radial. Therefore, we must respect the conditions in Section 3.5.1.

In this case, we introduce a binary variable $d(u, v)$ representing the state of the arc (u, v) (1 if ON (closed switch), 0 if OFF (opened switch)). The following constraint for radiality is imposed.

$$\sum_{(u,v) \in A} d(u, v) = N - N_{src} \quad (3.25)$$

As we have seen in Section 3.5.1, the fictitious flow needs to be added in order to ensure that each vertex is connected to a source.

The fictitious flow is presented below. The same constraints applied in Section 3.5.2 are used but, as we said, the underlying graph is seen as an oriented graph. Therefore, for each vertex u , we are dealing with its direct predecessors and successors.

$\forall u \in N_{non-src} :$

$$\sum_{v \in N^{in}(u)} f(v, u) - \sum_{v \in N^{out}(u)} f(u, v) = \mathbf{feq}(u) \quad (3.26)$$

$\forall u \in N_{src} :$

$$yfs(u) + \sum_{v \in N^{in}(u)} f(v, u) - \sum_{v \in N^{out}(u)} f(u, v) = \mathbf{feq}(u) \quad (3.27)$$

With:

$feq(u) = 1, \forall u \in N - N_{src}$, if $Peq(u) < 0 \cup \forall u \in N_{zi}$.

$feq(u) = 0$, for all other vertices, where $f(u, v)$ is the flow of the fictitious power in the arc (u, v) , $feq(u)$ is the value of the fictitious power consumed at vertex u , and $yfs(u)$ is the fictitious power injected at source u .

The following constraints consider the relation between the state of each arc and the flow of the fictitious power in that same arc:

$\forall (u, v) \in A :$

$$\mathbf{f}_{min} d(u, v) \leq f(u, v) \leq \mathbf{f}_{max} d(u, v) \quad (3.28)$$

Where f_{min} is the minimal fictitious flow. f_{max} is the maximal fictitious flow. These constraints assure that every DG and zero injection bus are connected to a source vertex.

3.6.2 Voltage constraints

The voltage variation in this MIQP model is another modelization for the drop voltage equation [Ram+05] that gives a result similar to the equation (3.15). In fact, in the MIQP with one binary variable per edge, we have an oriented-graph. Therefore, for a vertex u , it determines the expression of voltage variation basing on the type of the neighbors of u if they are direct predecessors or successors.

$\forall (u, v) \in A :$

$$\mathbf{Us}_{min} d(u, v) \leq yUs(u, v, u) \leq \mathbf{Us}_{max} d(u, v) \quad (3.29)$$

$$\mathbf{Us}_{min} d(u, v) \leq yUs(u, v, v) \leq \mathbf{Us}_{max} d(u, v) \quad (3.30)$$

$$\begin{aligned} \mathbf{Us}_{min} (1 - d(u, v)) &\leq Us(u) - yUs(u, v, u) \\ &\leq \mathbf{Us}_{max} (1 - d(u, v)) \end{aligned} \quad (3.31)$$

$$\begin{aligned} \mathbf{Us}_{min} (1 - d(u, v)) &\leq Us(v) - yUs(u, v, v) \\ &\leq \mathbf{Us}_{max} (1 - d(u, v)) \end{aligned} \quad (3.32)$$

Where $Us(u)$ is the voltage squared at vertex u . $yUs(u, v, u)$ is the voltage squared at bus u if the arc (u, v) is ON, otherwise it is 0. The same goes with $Us(v)$ and $yUs(u, v, v)$. Let U_N be the nominal voltage. Us_{min} is the minimal voltage squared and Us_{max} is the maximal voltage squared.

In order to let the solver able to limit the voltage values, additional constraints are applied allowing the computation of that voltage. First, the voltage at the sources (i.e. secondary of the HV-MV transformers) is fixed at a specific value:

$$\begin{aligned} \forall u \in N_{src} : \\ Us(u) = U_N^2 \end{aligned} \quad (3.33)$$

Then, starting from the source vertices, the voltage squared of the non-source vertices is computed, based on the voltage drop or increase due to the flow of active and reactive power in the lines's resistances and reactances:

$$\begin{aligned} \forall u \in N_{non-src} : \\ \sum_{v \in N^{out}(u)} (yUs(u, v, u) - yUs(u, v, v)) \\ + \sum_{v \in N^{in}(u)} (yUs(v, u, u) - yUs(v, u, v)) = \\ 2 \left[\sum_{v \in N^{out}(u)} \mathbf{R}(u, v) yp(u, v) + \mathbf{X}(u, v) yq(u, v) \right. \\ \left. - \sum_{v \in N^{in}(u)} \mathbf{R}(v, u) yp(v, u) + \mathbf{X}(v, u) yq(v, u) \right] \end{aligned} \quad (3.34)$$

Where $R(u, v) / X(u, v)$ is the *resistance/reactance* of the arc (u, v) . $yp(u, v) / yq(u, v)$ is the active/reactive power flowing through the arc (u, v) . In Constraint (3.34), we look at the neighbors of u depending on if they are a direct predecessor or successor of u . This constraint does not work if a loop is presented between two neighbors u and v ³ because v will be a direct successor and predecessor of u at the same time and thus, the voltage squared computed will not be true. The radiality constraints guarantee that there is no loop between two neighbors vertex.

3.6.3 Arcs and sources power limits and linearization

The active and power variables need to be related to the binary variables, so that for an arc (u, v) : The flow of active (resp. reactive) power is null if that arc is OFF, and is limited if the arc is ON:

³There will never be a loop between two neighbors because of the radiality constraints

$\forall (u, v) \in A :$

$$-S_{max(u,v)} d(u, v) \leq yp(u, v) \leq d(u, v) S_{max(u,v)} \quad (3.35)$$

$$-S_{max}(u, v) d(u, v) \leq yq(u, v) \leq d(u, v) S_{max}(u, v) \quad (3.36)$$

$\forall u \in N_{src} :$

$$-S_{source-max}(u) \leq yps(u) \leq S_{source-max}(u) \quad (3.37)$$

$$-S_{source-max}(u) \leq yqs(u) \leq S_{source-max}(u) \quad (3.38)$$

$yps(u)$ / $yqs(u)$ is the active/reactive power, that is injected(+) or absorbed(-) at source u , $S_{max}(u, v)$ is the apparent power limit of the arc (u, v) , and $S_{source-max}(u)$ is the apparent power limit of the source u .

As a reminder, the limitation of the combination of Constraints 3.35 and 3.36 , on the (yp, yq) plane, when the arc is ON is just an approximation of the "real" quadratic constraint $(yp^2 + yq^2 \leq S_{max}(u, v)^2)$ that do limit the apparent power flowing through an arc (u, v) . (Approximating a circle by a square). See Section 3.5.5 for more details.

The same approximation is done for limiting the apparent power flowing through the sources (3.37) and (3.38), similar to what is done for the branches.

3.6.4 Power Balance Constraints

As we have seen in the previous section, the power balance constraints can be written as follows, assuming that both the active and reactive losses of the branches and the parasitic capacitors, are neglected.

$\forall u \in N_{non-src} :$

$$\sum_{v \in N^{in}(u)} yp(v, u) - \sum_{v \in N^{out}(u)} yp(u, v) = P_{eq}(u) \quad (3.39)$$

$$\sum_{v \in N^{in}(u)} yq(v, u) - \sum_{v \in N^{out}(u)} yq(u, v) = Q_{eq}(u) \quad (3.40)$$

$\forall u \in N_{src} :$

$$yps(u) + \sum_{v \in N^{in}(u)} yp(v, u) - \sum_{\forall v \in N^{out}(u)} yp(u, v) = 0 \quad (3.41)$$

$$yqs(u) + \sum_{v \in N^{in}(u)} yq(v, u) - \sum_{v \in N^{out}(u)} yq(u, v) = 0 \quad (3.42)$$

3.6.5 Objective function

The objective function for the MIQP with bidirectional variables (Section 3.5) and the MIQP with one binary variable per edge is the same. It is quadratic, and can be written as follows⁴ :

$$\min Z = \frac{1}{U_{N^2}} \sum_{(u,v) \in A} R(u,v) [yp(u,v)^2 + yq(u,v)^2] \quad (3.43)$$

Thus, the optimization problem is a Mixed Integer Quadratic Programming (MIQP) problem.

⁴Using the approximation that the voltage is at its nominal value for every bus.

3.7 Challenges and contributions

The optimization *exact methods* have the advantage of being general and to prove the optimality, or the distance to the optimum of the proposed solution. However, they are very developed for linear or quadratic problems but advances are still necessary for the resolution of nonlinear problems. In addition, the convexity of the problem is a necessary condition for the use of certain solvers, the difficulty for the use of these techniques is therefore to model the problem in a linear or quadratic manner and convex. The inconveniences lie in the search space of solutions, which is all possible combinations of both binary and continuous variables which define all potential solutions. The point is that, with the increase of the number of decision and continuous variables (which depends on the size of the network), the complexity of the search space increases. Therefore, the solver's computational time for any MIQP formulation applied to that network will increase.

Here is the main goal of that thesis: reduce the solver's computational time for the MIQP formulation applied to the SRD distribution network. The contributions of this thesis use the academic and SRD networks as tests with the goal of decreasing the solver's computational time for the MIQP formulation.

Now, due to the large size of the SRD distribution network, which consists of 45147 buses with 16698 switches, there will be a total of 16698 binary variables, which is a large number. We can anticipate that the solver's computational time will be too long if we apply the MIQP formulation to the SRD network.

In conclusion, the contributions of this thesis aim to reduce the solver's computational time. The main idea is to reduce the search space of solutions, which ultimately decreases the solver's computational time. In fact, the solver's computational time depends on the size of the graph representing the network, typically on the size of the network. The load and generation in input for the MIQP, in these contributions, are a single tuple $(load, prod)$.

After these contributions, a generalization is made for the case of the single tuple of loads and generations: the case of load-curve-based optimization. We will study the different cases in this context, then discuss which is the best to maintain and solve the different barriers that can appear, especially with the high integration of decentralized generation. Another contribution, consisting of the integration of power curtailment into the model, is presented to address this. This contribution has an impact on maintaining voltage stability in the case of high integration of renewable energy and is tested on academic networks to validate the results obtained by the solver's computation.

Chapter 4

A network reduction method for the Distribution Network Reconfiguration problem

In the previous chapter, we have defined the objectives of the thesis and the roadmap of contributions. The work is focused on reducing computational time of the solver. In particular, the work is based on the Distribution Network Reconfiguration (DNR) which can be modeled using a Mixed Integer Quadratic Programming (MIQP) problem. For SRD, the objective is both to reduce the solver's computational time for the MIQP model that has been developed in [Ali17], while taking in account additional constraints like reactive power and control the voltage variation. We have stated this model in the previous chapter with additional features that has been proposed in the literature.

In this chapter, the first contribution of this thesis is proposed. The main goal is to reduce the solver's computational time for the MIQP model proposed in Chapter 3. The contribution is a network reduction method where the size of the underlying graph in input for the MIQP model is reduced having an equivalent underlying graph with a reduced size. The chapter presents in details the network reduction method. This method is tested on an agency of the SRD network.

4.1 Introduction

The Distribution Network Reconfiguration (DNR) problem is a challenging issue in the electrical field. This problem, known to be NP-hard [Hel+21], becomes increasingly complicated due to the large-scale size of the networks. The size of the instance significantly impacts the ability to find a solution for this problem using a solver. Therefore, employing reduced networks may aid in finding the optimal solution for the DNR problem. In this problem, binary variables represent the state of the switches as 1 for opened switch and 0 for closed one. The objective is to obtain the best configuration of switches that minimizes power loss while adhering to operating and electrical constraints. The DNR problem is modeled as a Mixed Integer Programming (MIP), and its resolution is not feasible in polynomial time unless $P = NP$. In the case of large-scale networks, the number of switches is substantial, leading to a considerable number of binary variables and increased computational time.

4.1.1 Literature review for reduction methods

In the literature, numerous network reduction methods exist. In [War49], the reduced network is constructed using the Gaussian elimination technique. In [NA14], a minimum spanning tree algorithm is proposed to reduce the network's size, aiming to facilitate the dynamic analysis of the feeders. In [JL91], a method of reducing a radial network into a single line is performed for load flow calculation and voltage stability analysis. Most of the methods mentioned above are effective for load flow simulations and voltage stability. The difference is that in this chapter, an algorithm is proposed to reduce the network's size into an equivalent one, which can be used as an instance of the DNR problem.

4.1.2 Roadmap of the chapter

In this chapter, a network reduction method is proposed for the DNR problem. The Mixed Integer Quadratic Programming (MIQP) model used is the MIQP with bidirectional binary variables that is detailed in Chapter 3 to represent the DNR problem. Subsequently, the effectiveness of the network reduction algorithm will be assessed in terms of quality of the optimal feasible solution (i.e power losses) and computational time for a large scale distribution network. We will remind briefly the details of the MIQP model that is applied later to the network reduction method.

4.2 Contribution: A network reduction method for the DNR problem

The main contribution in this chapter is to provide a methodology for network graph reduction. This reduction is called *network reduction*. This reduction, based on graph theory methods, tends to reduce the size of the underlying graph (representing the distribution network) that is the input of the MIQP model with bidirectional binary variables. It consists on the sequential removal of the vertices until reaching a cycle or a source in the underlying graph. After the presentation of the network reduction, another reduction taken from [Ali17] is performed. The experiments and comparisons before and after the application of these reductions will be performed in the next section.

The network reduction starts, sequentially, for each leaf and removes it if the cardinal of its neighbors is one and only one. if it is the case, the neighbor is selected and this process is iteratively done until reaching a selected vertex with 2 or more neighbors or a selected vertex which is a source. This selected vertex where the process terminates is called a terminal vertex. In Fig. 4.1, the terminal vertices are w_0 and *source*.

After doing this process on all leafs, it remains to verify if the voltage variation limits are respected of the removed subsets for each terminal vertex. This is done by running a linear program that is presented in the next section. In fact, without verifying the voltage variation limits on the removed sets, the method will not be valid.

As we can observe, in the network reduction, the set of removed vertices consists of the paths leading to leafs. In fact, those paths in the underlying graph are not useful for the MIQP model. The proof is, suppose the case where a switch is contained in one of those paths. All switches are closed in the underlying graph. After applying the MIQP as

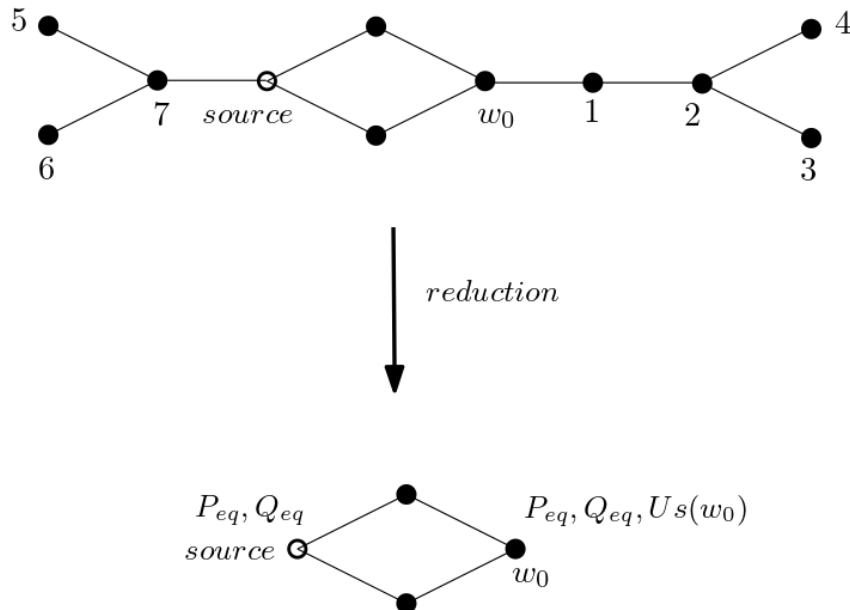


Figure 4.1: $\{1,2,3,4\}$ are merged into w_0 and $\{5,6,7\}$ into the source

the underlying graph in input, if this switch changes its state, then the end of this path will be disconnected. Therefore, the switches contained in those paths will remain closed in the feasible solution given by the MIQP and the removal of the whole path will reduce the binary variables representing those switches together with the continuous variables for each edge in this path.

So, by removing those paths, the feasible solution of the MIQP that takes the equivalent graph as input will not be affected.

The flowchart of the algorithm of network reduction is presented in Fig. 4.2.

4.2.1 Algorithm of network reduction

The network reduction generates the sets $S(l)$ for each leaf l (cf. Fig. 4.2). Those sets will be used in the next step to identify the minimal and maximal voltage variation. Let G be the initial graph. For a leaf l_0 in G , let S_{l_0} be its set generated by the algorithm. Let G_0 be the subgraph of G induced by S_{l_0} . The set S_{l_0} is removed by the algorithm from G except one vertex that has not been removed from G_0 . This vertex is a terminal vertex that has two or more neighbors after the removal of the edge that belongs to the path to l_0 , or could be a source (As we said in the previous section). Let w_0 be this vertex. This vertex can be either a source or a non-source vertex. After the obtention of the reduced graph by applying the algorithm on G , the model presented in this chapter is applied to the final graph. But before this application, we need to determine further information on that vertex w_0 .

The goal is to have an equivalent network (graph) to the initial one. After applying the network reduction, and the removal of the sets $s(l)$ associated to each leaf l , we have to determine the equivalent active and reactive power at the terminal vertex in the set $S(l)$ and the minimal and maximal voltage values at this vertex.

Let w_0 be the terminal vertex of the path from a leaf l_0 until the arrival to a cycle or a source as in Section 4.2.1. G_0 is the subgraph in G induced by the set S_{l_0} (Section 4.2.1). Therefore, w_0 could be either a source or a non-source vertex.

Suppose that w_0 is a source in G , then G_0 is merged into the source vertex. The active and reactive power amount (P_{eq} and Q_{eq}) are calculated in G_0 at w_0 (Fig. 4.1). This can be simply done by applying constraints (3.6), (3.7), (3.8) and (3.9) to G_0 where the branches are all with a closed state (otherwise some vertices won't be connected to a source). The resolution consists of the sets of linear equations which can be solved using linear algebra techniques. In this case, the voltage constraints are not taken into account, due to the fact that there is a unique path from the leaf l_0 to the source w_0 in this case and assuming that the network is well dimensioned. So, the voltage are supposed to not be violated from l_0 to w_0 .

Now, suppose that w_0 is not a source. Then, G_0 is merged into w_0 as we know. Therefore, on top of using constraints (3.6), (3.7), (3.8) and (3.9) and supposing that w_0

is a source vertex in those equations, the aim is to compute the voltage bounds at w_0 to use them in the MIQP applied to the reduced network. To achieve this, a new voltage limit for that vertex is defined. These bounds are used in the global optimization, where the model proposed in Section 3.5 and is applied to solve the DNR problem for G . Two linear programming applied to G_0 are solved using the constraint (4.1).

$\forall u \in G_0$ such that $N^{in}(u) \geq 1, \forall v \in N^{in}(u)$:

$$Us(u) = Us(v) - 2(R(u, v)yp(v, u) + X(u, v) yq(v, u)) \quad (4.1)$$

The first linear program will find the lower bound of the voltage at w_0 using the

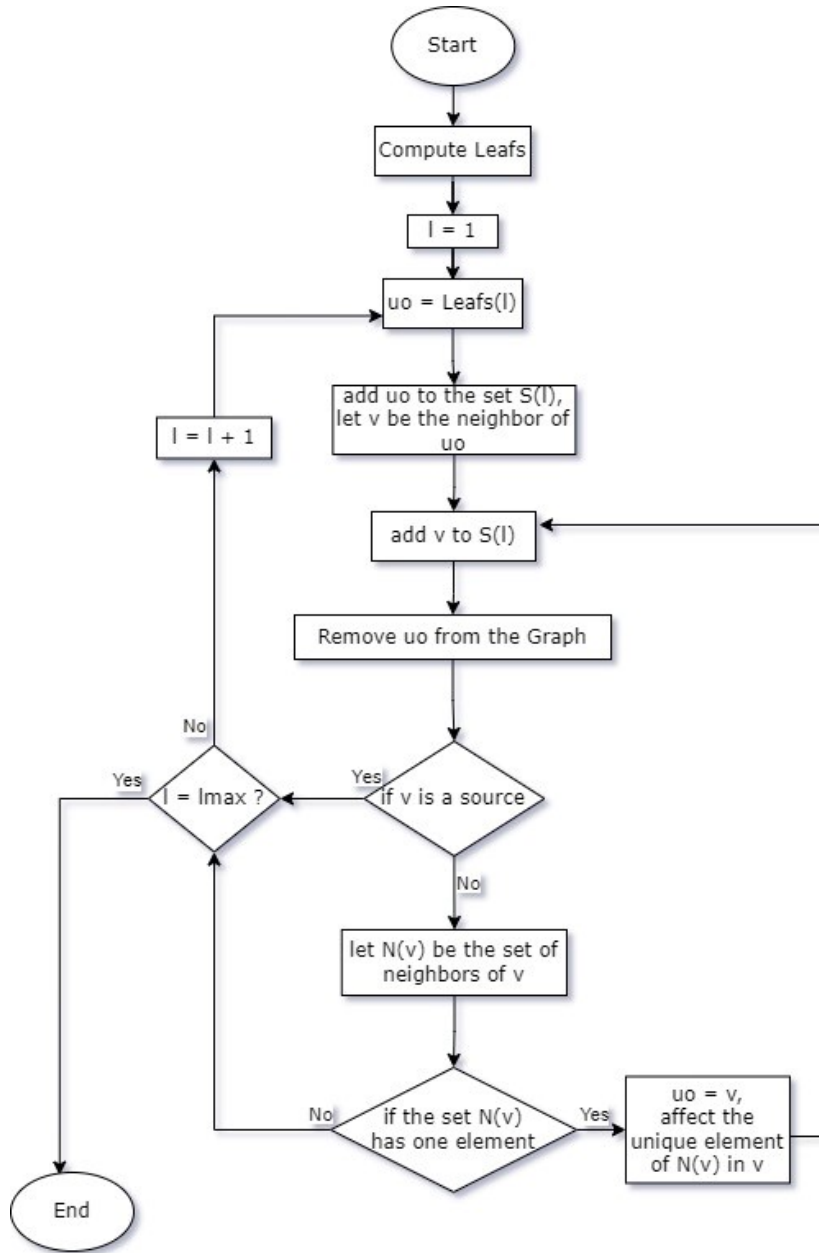


Figure 4.2: Flowchart of network reduction

previous constraint (4.1) within the following objective function:

$$\min Z_{\text{resolve}} = Us(w_0) \quad (4.2)$$

The second linear program will as well as for the lower bound, the upper bound of voltage at w_0 is obtained with (4.1) and

$$\max Z_{\text{resolve}} = Us(w_0) \quad (4.3)$$

We remind that $N^{in}(u)$ is the set of direct predecessors of u . So, those two linear programs will launch the constraint (4.1) on the graph G_0 together with the power equations constraints where the variables yp and yq will be served for (4.1) to compute the voltage at each vertex of G_0 . For a graph G_0 of n vertices, the set of constraints (4.1) for each vertex has n equations, so we could obtain a solution of the voltage at w_0 which is $Us(w_0)$ but this is not guaranteed as the minimal or maximal one. Therefore, this emphasize the need of the formulation of a linear program and not only solving the set of voltage constraints only by solving the system of equations.

Another ending criteria is the case of the paths that, starting from a leaf, lead to a source. As a reminder, a source in the SRD network is considered as a HV/MV transformer and this distribution networks present some department that are connected only to the source without any cycle. The idea behind this ending is to prevent from the deletion of the source, which is not accepted because the goal of this reduction is to have an equivalent network to the initial one.

4.2.2 Reduction from [Ali17]

After obtaining the reduced graph, another reduction as performed in [Ali17] is applied. It consists of merging the non-controllable branches in series, that include no loads or generations vertices, into one edge. The new edge has an equivalent resistance/reactance, which is the sum of the resistance/reactance of merged branches, and a maximal capacity of apparent power flow that equals the minimal capacity of apparent power flow among the merged branches.

4.3 Experiments

In this section, the network reduction and Reduction from [Ali17] are tested on a large scale agency from SRD distribution network [Kar]. The solver used is Gurobi Optimizer version 10.0.1 with two modified parameters : MIPGap [Gurb] (relative optimality gap) and Heuristics [Gura] set to 0. The aim behind this is to ensure that the solver will terminate once an optimal solution is found (MIPGAP) and with no supplement heuristics that will tend to reduce the search space. This computation is done on a computer equipped with an Intel(R) Core(TM) i5-9500 CPU @ 3.00GHz with 32 GB of RAM. The MIQP with bidirectional binary variables presented in the Section 3.5. We will compare the solver's computational time for this MIQP on the agency before and after reduction, in order to interpret the efficiency of the network reduction methods in terms of the solver's computational time.

4.3.1 Settings

The following parameters for the network are used: the load (respectively the DG) power is equal to 13% (respectively 25%) of the maximum power, with a ratio of reactive power to active power of 20% (respectively 0%). The transformers are considered as simple branches with zero impedance. The capacitors of the lines are removed from the power flow simulation. The 15% voltage limit must be respected on the medium voltage vertices only. The nominal voltage of the medium voltage side of the network is 20 KV. The voltage of the source is put to 1.03 per unit (p.u). The voltage per unit value is defined as the actual voltage divided by the nominal voltage. It is a sort of normalization for the voltage at each node with respect to the nominal voltage. For example, The nominal voltage is 1 p.u. The initial power loss is the amount of power loss computed on the initial configuration. It is computed using Pandapower, an opensource python library [Thu+18]. The final power loss is the amount of power loss on the feasible configuration (or the solution). It is computed using Pandapower on the feasible (optimal) configuration (solution) given by the MIQP with bidirectional binary variables per edge. Table 4.1 shows the results of the numerical experiment.

The initial power loss is equal to 60.05 kW, and for the four different cases, the final power loss amounts to 44.85 kW, meaning that there is a reduction in power loss of -25.32%. The result shows that the reduced networks are all equivalent to the initial one in terms of power loss reduction when solving the DNR problem. In addition, the voltage for each vertex respects the limit 15% of variation. (1.0181 p.u is the minimum and 1.03 p.u is the maximum).

Table 4.1: Experiments on an agency of SRD

	Time (s)	Number of vertices	Reduction of vertices (%)	Number of switches
Before reduction	68.43	2588	-	403
network reduction	63.86	527	-79.54	132
Reduction from [Ali17]	60.45	1745	-32.57	403
network reduction then Reduction from [Ali17]	51.48	424	-83.62	132

4.3.2 Interpretations

From Table 4.1, the Reduction from [Ali17] does not have an impact on the number of switches (403 before and after the reduction), but still reduces the computational time (68.43 seconds (s) to 60.45s). This can be explained by the reduction of the number of continuous variables induced by Reduction from [Ali17] (reduction of vertices by 32.57%).

In addition, network reduction has a relatively important impact on the reduction of the number of switches (403 to 132), as well as a great reduction in the number of vertices (-79.64%), but the reduction in the computational time (from 68.43s to 63.86s) is neither proportional to the reduction of the number of switches nor to the reduction in the size of the network. And finally, applying network reduction followed by Reduction from [Ali17] gives the best results in terms of the reduction of vertices (-83.62%) and a computational time (from 68.43s to 51.48s). It is worth mentioning that the different durations included in Table 4.1 do not include the time required to perform pre-solves. The pre-solves time is the same for each case in Table 4.1.

4.4 Conclusion

A network reduction method is proposed for the MIQP with bidirectional binary variables that conserves the total power in the network while respecting the voltage limits by creating an equivalent network. The best result (without taking the pre-solve time into account) is obtained by performing the two reductions sequentially, resulting in better computational time for resolving the DNR problem formulation and increased effectiveness in dealing with large-scale networks. This method has the potential for utilization if it produces superior results compared to no graph reduction in terms of solver's computational time. Further investigations are needed to understand why it increases computational time in some cases. Furthermore, this reduction method can be tested on a DNR problem with additional constraints.

In the next chapter, a Low-Impact Switch Elimination Method is presented that has the goal to reduce the solver's computational time by detecting the most impactful switches.

Chapter 5

Low-Impact Switch Elimination Method for Distribution Network Reconfiguration for Large-Scale Networks

The Distribution Network Reconfiguration (DNR) consists in modifying the topology of a Distribution Network (DN) by changing the state of its switches, thereby altering the power flow path. In this thesis, DNR is used to minimize losses while satisfying certain topological and electrical constraints. For large-scale DNs, like the SRD distribution network, this problem can be challenging to solve because the number of switches (and thus the number of binary variables) becomes significant, leading to a combinatorial explosion.

In the previous chapter, we presented a network reduction method that reduces the size of the graph representing the network, thereby reducing the number of variables and constraints, and consequently, their impact on the solution's search space. The ultimate goal is to reduce the solver's computational time for the Mixed Integer Quadratic Programming (MIQP) formulation of the DNR problem.

In this chapter, we present a contribution aimed at decreasing the solver's computational time. It involves a method to identify the most impactful switches for the DNR problem. The most impactful switches remain as binary variables, while the binary variables of the less impactful switches are converted into input data (either ON or OFF) to maintain their state. This approach effectively reduces the number of binary variables, thereby decreasing computational time. The method's performance is evaluated using a simulation on a realistic 2,588-bus SRD distribution network. The results show that the proposed method can reduce the computation time of the DNR by a factor of up to 177.

5.1 Literature review

In distributions systems with manually controlled switches, switches cannot be operated frequently due to the cost of each operation. Therefore, constant load models peak (or mean value) are considered for the most of the reconfiguration studies [CCS05], [TYF13], [SL03]. In particular, [TYF13] proposes an approach to find the optimal configuration under peak load only. In the context of smart grids, manual switches that have the most impact on the system performance can be identified and substituted with remote-controlled switches [SL03], [JV12]. Therefore, the method presented in this chapter can be used in the identification of these manual switches. However, frequent switches operations may be cost, can tend to reduce system reliability and create voltage violations [Spi+12]. Moreover, the substitution of all manual switches with smart switches may be economically infeasible [Bou+10], [GKE14].

5.2 Low-impact switch elimination method

In complex electrical networks, the numerous switches can occasionally complicate operations and reduce system efficiency. Simplifying these electrical distribution networks by classifying the switches based on their functional roles would significantly reduce power losses. Many of the switches are intended for redundancy in emergency situations, having little impact on the everyday efficiency of the network.

In contrast, there are parallel switches that act like "highways", playing a critical role in maintaining optimal power flow while minimizing losses. By focusing on these highway switches, we can simplify network operations and enhance system efficiency and reliability. The low-Impact switch elimination method proposed in this chapter identifies these highway switches, even though the network cartography does not explicitly indicate their status as such.

In this section, the low-Impact switch elimination method for the simplification of the switches is presented.

The intuition is that not all the switches of the Distribution Network (DN) are useful for the Distribution Network Reconfiguration (DNR). A set of initial Operating Points (OPs) is chosen, where each OP has specific values as coefficients for loads and Distributed Generations (DGs) at each point in the network. The concept of this method is to execute the DNR sequentially at each initial OP, and then, for each OP, a continuous value $\in [0, 1]$ is determined for each switch in the network. Finally, each switch is classified as a most impactful switch or not. The most impactful switches will remain as binary variables in the MIQP with one binary variable per edge, and the remaining switches will be fixed in their state (1 or 0). One of the challenges is selecting a set of initial OPs that is representative of all possible scenarios of load and production (e.g., high load, low production). For the $j - th$ OP:

$$\forall u \in N_{non-src} :$$

$$P_{load}(u) = k_{load}(j) P_{load-max}(u) \quad (5.1)$$

$$P_{DG}(u) = k_{DG}(j) P_{DG-max}(u) \quad (5.2)$$

Where $k_{load}(j) / k_{DG}(j)$ represents the coefficient of the $j - th$ OP used to select the power of the load / DG at bus u , from the maximum possible power of load / DG ($P_{load-max}(u) / P_{DG-max}(u)$) at bus u . These coefficients are independent of the buses, meaning that it is assumed that the power of the loads for all buses, between two different OPs, vary the same way, e.g., if the value of $k_{load}(j)$ doubles, then the power consumed by the loads of each bus will double as well. The same is true for DGs.

Once the initial OPs are chosen, the MIQP with one binary variable per edge is applied **sequentially** on all of them. The DNR in this chapter is considered as the MIQP with one binary variable per edge presented in Chapter 3, in the Section 3.6.

After obtaining the results of the DNR: $SW_ON(u, v)$ is computed, which represents, for each switch (u, v) , the average value of being ON (in percentage) for the DNRs conducted with the initial OPs:

$$\forall(u, v) \in A_{SW} :$$

$$SW_ON(u, v) = 100 \cdot \frac{\sum_{j=1}^{NIOP} D(u, v, j)}{NIOP} \quad (\%) \quad (5.3)$$

Where NIOP is the Number of Initial Operating Points, and $D(u, v, j)$ represents the state of the switch (u, v) (which is $d(u, v)$) that is obtained through the DNR applied on the $j - th$ initial OP.

Then, iterating over all the switches, the following can be done:

- If a switch (u, v) has a value of $SW_ON(u, v) = 100\%$, then it is considered as not really impactful for the DNR (because it was ON all the time and never changed), and is assigned as an ON arc that is not controllable: $d(u, v) = 1$.

- If a switch (u, v) has a value of $SW_ON(u, v) = 0\%$, it is also considered as not impactful for the DNR (because it was OFF all the time and never changed), and is set as an open arc in the DNR: $d(u, v) = 0$.

- If a switch (u, v) has a value of $SW_ON(u, v) \in]0\%, 100\%[$, then it is considered as impactful for the DNR (because its state was varying): **$d(u, v)$ is kept as an optimization variable¹**, and the switch (u, v) is included in the set SW_OV (for Switch Optimization Variables), which represent the set containing all the switches that are considered as impactful.

While one could argue that the bounds on the interval could be in $]min\%, max\%[$ with $min\% > 0$ and $max\% < 100$, our tests on real NR showed that gains were already significant with $]0\%, 100\%[$. In this case, moreover, the loss in performance of the optimization

¹Thus, its value needs to be determined by the optimization.

is expected to be negligible. Further studies could be conducted to evaluate, for an interval $[\min\%, \max\%]$, how much degradation of performance to expect with this reduction of the search space, depending on the values of min and max.

5.3 Experiments

The solver used is Gurobi Optimizer version 10.0.1, on a PC with 11th Gen Intel(R) Core(TM) i5-1135G7 @ 2.40GHz 2.42 GHz 8,00 GB of RAM. The Pandapower [Thu+18] library of Python is used to perform Power Flows (PFs) on the DNs.

The proposed method is tested on a realistic agency of the SRD distribution network composed from 2588-bus DN that can be obtained from [Kar] and tested in the network reduction method in the Chapter 4, with 403 switches. After performing the network reduction method in the previous chapter, it remains 132 switches. The others which are removed after the reduction, are considered ON².

The voltage at the source is set at 1.03 *p.u.*. For all the different optimizations, the ratio of reactive power to active power for all loads is 0.1, and the one for all DGs is 0³.

The simulations can be separated into three phases:

1- **A first phase** where the identification of the most impactful switches is performed.

2- **A second phase** where the optimization of the network with only the most impactful switches is performed.

3- **A third phase** where the results obtained from the DNR with most impactful switches are compared with a classical DNR where the whole set of switches as binary variables.

Phase1: For this phase, six different OPs are chosen in the (k_{load}, k_{DG}) plane, in a way to ensure a "broad" distribution, i.e. the OPs are not close to each others, so as to capture the "global behavior" of the switches in the network, and not just on a specific zone of the plane. The OPs can be viewed in Table 5.1 as well as in Fig. 5.2. They have been chosen to be representative of the scenarios of strong load and low generation (0.18,0.2), low load and strong generation (0.06,0.8), as well as both strong load and generation (0.2,0.8). The choice of loads in a representative manner may require the intervention of experts. Alternatively, historical consumption-based datasets could be used, but this is out of the scope of this thesis. Then, the DNR is run on these OPs **sequentially**. As a result, a curve showing the average percentage of being ON for each switch can be seen in Fig. 5.1.

A time limit of 9000 seconds is set in the Gurobi solver ($TimeLimit = 9000$). Only the second initial OP $(k_{load}, k_{DG}) = (0.05, 0.2)$ was not able to reach optimality within

²The other switches are necessarily ON, because if they are OFF, certain buses will not be connected to a source.

³Meaning that when selecting an OP and modifying the active power, then the reactive power is modified as well.

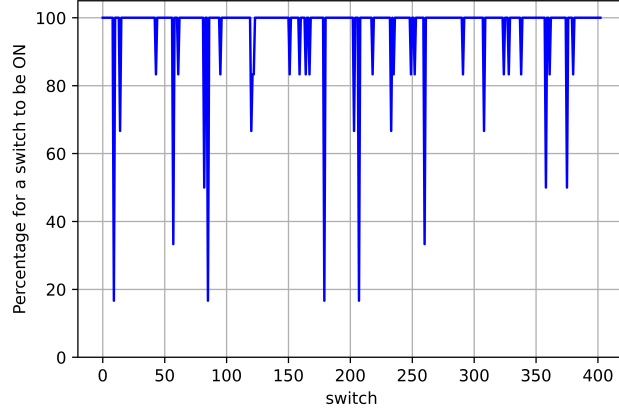


Figure 5.1: Percentage for switches of being ON (closed).

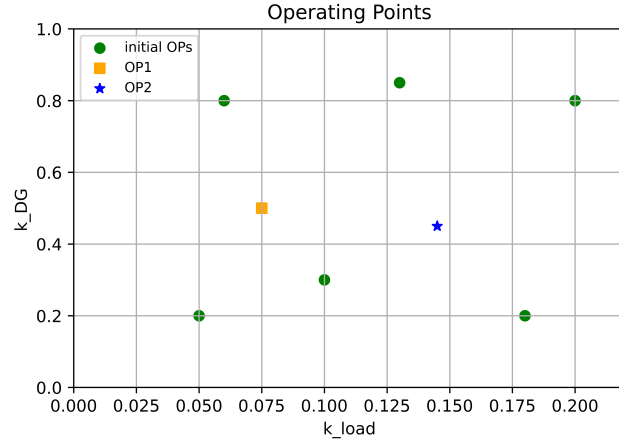


Figure 5.2: Scatter plot of the initial OPs + OP1 + OP2.

Table 5.1: Initial OPs

k_{load}	k_{DG}
0.05	0.2
0.06	0.8
0.18	0.2
0.2	0.8
0.1	0.3
0.13	0.85

the specified time limit: it converged with a gap of 1.73%. Note that since the operation can be done only once until some topological change in the agency of the network, the time limit could be relaxed.

The following data are displayed in Table 5.2. As it can be seen, for the 6 initial OPs, among the 403 switches of the DN, only 33 are varying (8.19%), and 370 of them (91.81%) are fixed, which means that, at least for these OPs and this DN, the vast majority of the switches do not contribute to the DNR, in the sense that they can be taken as fixed

Table 5.2: Results for the switches

	Switches number	Percentage (%)
Varying switches	33	8.19
Fixed switches	370	91.81
Always ON switches	370	91.81
Always OFF switches	0	0.0

Table 5.3: OP1 and OP2

	k _{load}	k _{DG}
OP1	0.075	0.5
OP2	0.145	0.45

Table 5.4: Results for OP1 and OP2

	Final Losses (kW)	Loss Reduction (%)	Time (s)
Classical DNR OP1	6.34	-38.17	730.9
Simplified DNR OP1	6.34	-38.17	8.17
Classical DNR OP2	41.66	-27.90	506.6
Simplified DNR OP2	41.66	-27.90	2.86

values instead of optimization variables. We also notice that the fixed switches are all ON (370), and none of them is always OFF. The set of the varying switches SW_OV is also obtained.

Phase2: For the second phase, two new OPs are considered, called OP1 and OP2, and can also be seen from Fig. 5.2 and displayed in Table 5.3. They are selected in a way to ensure a sufficient distance from the six initial OPs, preventing bias in the simulations. Then, a simplified DNR with reduced switches is applied for both OP1 and OP2.

Phase3: For this last phase, a classical DNR with all the switches is applied for OP1 and OP2.

For OP1, the initial losses (before the reconfiguration) are **(10.26 kW)**, and for OP2, they are **(57.79 kW)**. The results can be seen in Table 5.4.

As can be seen from Table 5.4, which displays the results of four different optimizations, both the classical and simplified DNR converged to the same solution for both OP1 and OP2, despite the fact that the simplified DNR controls only 33 switches instead of 403 switches⁴. However, in terms of solver's computational time, it is clear that the simplified DNR is much faster than the classical one: **89.46 times faster** for OP1 and **177.16 times faster** for OP2, clearly showing the advantage of the proposed method.

In this section, **phase 3** was performed to ensure that the solution given by the simplified DNR reached optimality. However, skipping **phase 3** and directly using the solution of the simplified DNR as a MIP Start for the classical DNR is also possible.

⁴Or 132 switches if we only count the "truly" useful switches.

5.4 Conclusion

In this chapter, a low-Impact switch elimination method was proposed to find the most impactful switches in terms of DNR and use them as optimization variables, while setting the state of less impactful switches as fixed (ON or OFF) to reduce the number of binary variables and speed up computational time.

After an initial phase where six OPs were used to identify those impactful switches, the simplification method was tested on two OPs for a 2,588-bus realistic network. The results showed that the proposed method greatly improved computational time, making it roughly **177 times faster** in the case of OP2.

Thus, we have proposed two methods aimed at reducing the solver's computational time. The method in this chapter performed better than the network reduction method after testing them on a segment of the SRD distribution network.

Future work should include tests on more DNs with more OPs and the use of the MIP Start⁵ with the solution obtained by the simplified DNR as input to check if optimality is reached. If not, the solver should be allowed to achieve it. Additionally, the investigation of this improved speed for other applications of DNR, such as in real-time scenarios or dynamic reconfiguration, should also be carried out.

Till this chapter, the case of a single point (instant) of $(load, prod)$ has been tackled. The result is a single feasible configuration which is an optimal one. The goal was to reduce the solver's computational time to obtain the solution. In the next chapter, a generalized case will be studied: the case of dynamic loads and productions, and its advantages in comparison with a single point as well as its effect on the solver's computational time. Many cases of load-curve-based optimization for the DNR problem will be studied.

⁵Consists of pairs of variables and values hints to help the solver find an initial solution. These hints consist , known as a MIP start

Chapter 6

Load Curve-Based Optimization

In the previous chapters, we dealt with the case of a single time point load data. We were restricted to the scenario where we had an equivalent power value at one specific point in time, defined for each point in the network. This can be viewed as static loads and generation across the electrical network. The goal was to reduce the solver's computational time for this case. After these attempts, the case of static loads can be generalized into load curves, where the optimization provides a single feasible configuration. This configuration may not be optimal for each time point, but it does not violate the constraints associated with each time in the given set.

In this chapter, we will extend the Single Reconfiguration at a single operating point (single time) that was studied in the previous chapters, where methods to reduce the solver's computational time were presented for this case.

6.1 Introduction

Most Distribution Network Reconfiguration (DNR) approaches proposed in the literature only consider a single operating point (OP). However, since in the previous chapters we have proposed methods to greatly reduce the solver's computational time for an OP, we wonder if it is worthwhile to work with load/production curves. In the context of load curve-based optimization, time-varying loads and the variable output of distributed generation are considered. The idea here is to choose a given feasible configuration during a pre-defined time interval (day or week(s)) based on load and production forecasts, such that losses over time are minimized.

On the other side, the switches contained in distribution networks are either manual or automatic switches. To control a manual switch, an agent must physically travel to the site to change it, incurring a cost. Moreover, a switch has a lifespan determined by the number of times it is operated. Therefore, changing a switch's state has a cost. Therefore, it is crucial to find a way that, in case of the presence of load and generations curve, to find a feasible configuration that respects the constraints at a pre-defined time interval.

In the previous chapters, we have dealt with the *Single Reconfiguration* case where the set of times is a singleton. We did not say before that the set of times is singleton, it can be seen at that way. At this singleton, a reconfiguration that is made and an optimal feasible configuration is given by the solver using by one of the Mixed Integer Quadratic Programming (MIQP) defined in Chapter 3, Section 3.5 and 3.6.

Now, a generalization can be introduced where we have a set of times instead of a single one (the case where the optimization is applied on load and generation curves instead of a single tuple (*load, generation*)). Let $T = \{t_0, t_1, \dots, t_n\}$. For τ , which can be a day or a week or any period of time, a feasible configuration can be obtained that is optimal for a time $t' \in T$ and is not optimal for other $t \in T$ without violating the constraints in τ . This generalization is called *Fixed Reconfiguration*. If two or more than one feasible configuration are imposed to be obtained among T , this case is called *Multiple reconfigurations with operational constraints*. The operational constraints here state the maximum number of the feasible reconfigurations ψ_{max} . For example, for the whole set of times T , the $\psi_{max} = 3$ in Fig. 6.1. That is to say, we will obtain three feasible configurations for the whole set T .

The third case is named as *Free Multiple Reconfigurations* where no operational constraints are imposed. In other words, at each time $t \in T$, we have an optimal feasible configuration. This way of reconfiguration has many technologic and economics disadvantages. In fact, frequently manipulating the manual switches leads to increased maintenance and operational costs. Moreover, it requires more frequent system monitoring and adjustments by operators. On the other side, it requires significant investments in advanced control systems and real-time data acquisition.

The advantage of the Fixed Reconfiguration is that we have less binary variables than the case of a free reconfigurations without a limit of the number of reconfigurations. Therefore, a better computational time for the solver to find the optimal solution. But, the disadvantage can be seen in case we have a remarkable difference in loads or producers between two instants t_1 and t_2 . In this case, the topology can reduce power losses for t_1

and not t_2 . The solver will therefore choose the one that has the lower objective function. The voltage variation limits and other constraints remain respected.

We will review the existing literature on the DNR problem applied on load and generation curves (dynamic DNR). As in the case of the static DNR problem (one time's loads and generation), the methods are classified into deterministic, heuristic, and metaheuristic methods.

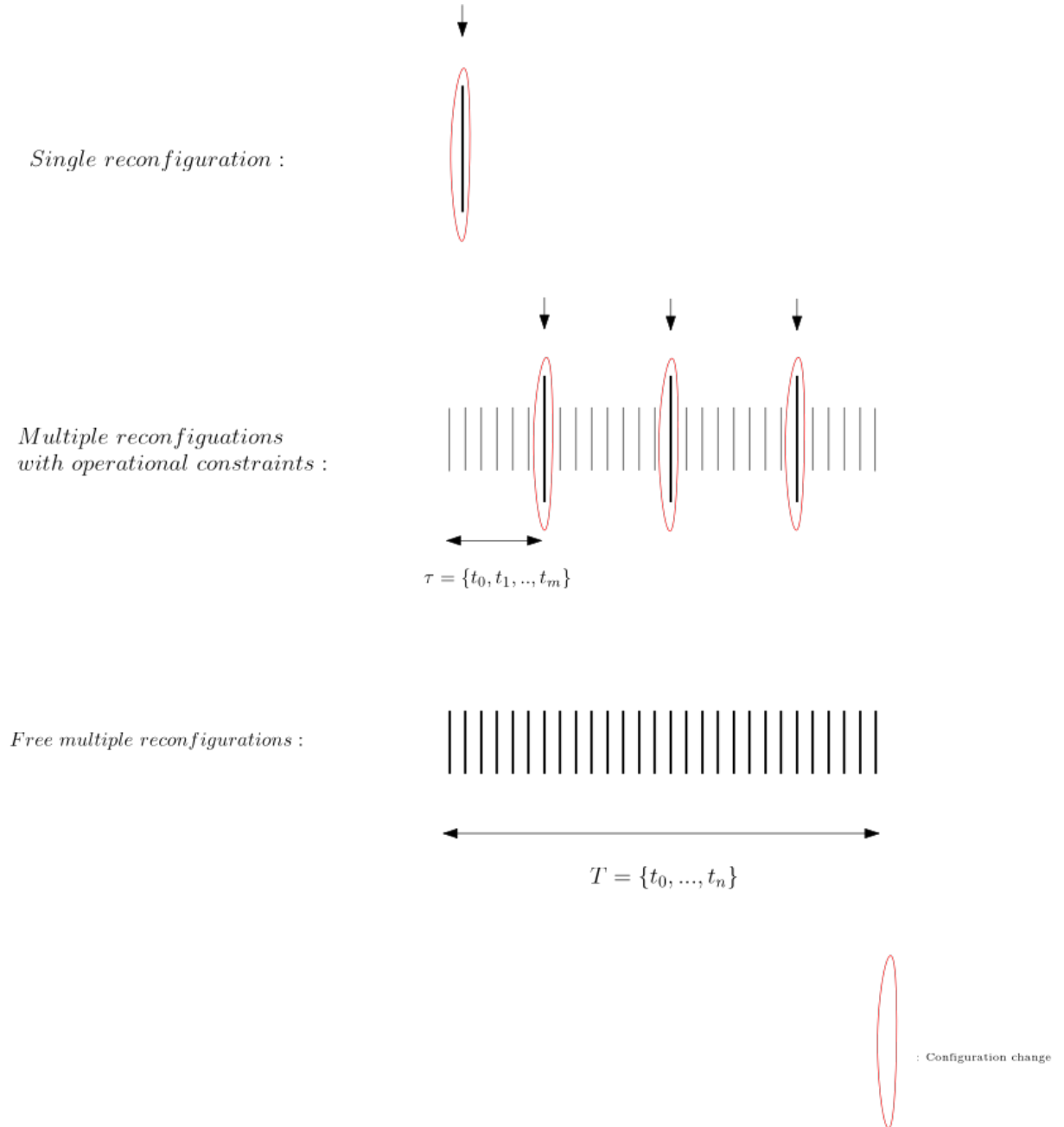


Figure 6.1: Optimization on load and generation curves

6.1.1 Literature Review

In the existing literature, various methods for the dynamic DNR problem are presented. In [Tou+15] and [Zha+18], the authors employ a method based on a Mixed Integer Linear Programming (MILP) model, both with and without DGs. In [Mos+17], the authors apply the minimum spanning tree algorithm to the dynamic DNR problem to minimize power losses. A spanning tree for a graph is a tree that covers (contains) all the vertices of the graph. The concept of this method is to first search for a spanning tree, then compute the power losses and identify the best configuration within this context.

Meta-heuristics have been used to solve the dynamic DNR problem to minimize power losses and maintain voltage stability. In [Xu+16], the authors consider a quantum particle swarm algorithm to find a configuration that reduces power losses. In [Wen+18], the authors propose a method based on particle swarm optimization to find the best network configuration for power loss minimization and voltage profile enhancements. Nevertheless, these methods cannot guarantee optimality.

Now, we will present the Fixed Reconfiguration and the Free Multiple Reconfigurations models. The multiple reconfigurations with operational constraints model is then introduced, with additional constraints to impose a maximum number of feasible configurations over a set of time instants for the Free Multiple Reconfigurations model.

6.2 Mathematical Model

Let $G = (V, A)$ be the underlying graph of the network. Let $P_{eq}(u, t)$ (resp. $Q_{eq}(u, t)$) be the equivalent active (resp. reactive) power at vertex u at time t . $yp(u, v, t)$ is the active power through the arc (u, v) at time t . $yq(u, v, t)$ is the reactive power through the arc (u, v) at time t . All variables remain the same as in Chapter 3, Section 3.6 with an addition of the time t in the chosen time window: if the predictions of the loads and generations are given every 10 minutes, and the time window is the next hour, then t will take six values, from now + 10 minutes to now + 60 minutes.

6.2.1 Fixed Reconfiguration model

In this subsection, the *Fixed Reconfiguration* is presented. In this case, we will have only one feasible configuration for all times $t \in T$ where T is a set of times. This is obtained by imposing the same radiality constraint for the MIQP with one binary variable per edge used in the Section 3.6, Constraint (3.25). Here, the binary variables d do not depend from the time t and a single feasible configuration is obtained for a set of times T .

As in the Chapter 3, Section 3.6, the fictitious flow should be added.

The following constraints correspond to Constraints (3.26), (3.27) and (3.28). The binary variables d do not depend from the time.

$$\forall t, \forall u \in N \setminus N_{src} :$$

$$\sum_{v \in N^{in}(u)} f(v, u, t) - \sum_{v \in N^{out}(u)} f(u, v, t) = f_{eq}(u, t) \quad (6.1)$$

$$\forall t, \forall u \in N_{src} :$$

$$yfs(u, t) + \sum_{v \in N^{in}(u)} f(v, u, t) - \sum_{v \in N^{out}(u)} f(u, v, t) = f_{eq}(u, t) \quad (6.2)$$

$$\forall u \in N_{src} \cup \forall u, P_{eq}(u) > 0 : f_{eq}(u) = 0$$

$$\forall u \in N_{src} \cup \forall u, P_{eq}(u) < 0 : f_{eq}(u) = 1$$

For each branch (u, v) and $\forall t$:

$$-f_{max}(t) \cdot d(u, v) \leq f(u, v, t) \leq f_{max}(t) \cdot d(u, v) \quad (6.3)$$

$$f_{max} = \sum_{\forall u \in N} f_{eq}(u, t) \quad (6.4)$$

Voltage variation constraints

The time t is integrated for the same constraints in the Chapter 3, Section 3.6. The following constraints correspond to Constraints (3.29), (3.30), (3.31) and (3.32). As it is known, d does not depend from the time t .

$\forall t, \forall (u, v) \in A :$

$$Us_{min} \cdot d(u, v) \leq yUs(u, v, u, t) \leq Us_{max} \cdot d(u, v) \quad (6.5)$$

$$Us_{min} \cdot d(u, v) \leq yUs(u, v, v, t) \leq Us_{max} \cdot d(u, v) \quad (6.6)$$

$$\begin{aligned} Us_{min}(1 - d(u, v)) &\leq Us(u, t) - yUs(u, v, u, t) \\ &\leq Us_{max}(1 - d(u, v)) \end{aligned} \quad (6.7)$$

$$\begin{aligned} Us_{min}(1 - d(u, v)) &\leq Us(v, t) - yUs(u, v, v, t) \\ &\leq Us_{max}(1 - d(u, v)) \end{aligned} \quad (6.8)$$

The following constraints correspond to the Constraints (3.33) and (3.34). $\forall t, \forall u \in N_{src}$:

$$Us(u, t) = U_N^2 \quad (6.9)$$

$$\begin{aligned} &\sum_{v \in N^{out}(u)} (yUs(u, v, u, t) - yUs(u, v, v, t)) \\ &+ \sum_{v \in N^{in}(u)} (yUs(v, u, u, t) - yUs(v, u, v, t)) \\ &= 2 \left(\sum_{v \in N^{out}(u)} R(u, v) \cdot yp(u, v, t) + X(u, v) \cdot yq(u, v, t) \right. \\ &\quad \left. - \sum_{v \in N^{in}(u)} R(v, u) \cdot yp(v, u, t) + X(v, u) \cdot yq(v, u, t) \right) \end{aligned} \quad (6.10)$$

Branch limit

From Chapter 3, Section 3.6, the following constraints correspond to (3.35) and (3.36).

$\forall t, \forall (u, v) \in A :$

$$\begin{aligned} -Smax(u, v) \cdot d(u, v) &\leq yp(u, v, t) \\ &\leq d(u, v) \cdot Smax(u, v) \end{aligned} \quad (6.11)$$

$$\begin{aligned} -Smax(u, v) \cdot d(u, v) &\leq yq(u, v, t) \\ &\leq d(u, v) \cdot Smax(u, v) \end{aligned} \quad (6.12)$$

$$\begin{aligned} -\sqrt{2} \cdot Smax(u, v) \cdot d(u, v) &\leq yp(u, v, t) + yq(u, v) \\ &\leq \sqrt{2} \cdot Smax(u, v) \cdot d(u, v) \end{aligned} \quad (6.13)$$

$$\begin{aligned} -\sqrt{2} \cdot Smax(u, v) \cdot d(u, v) &\leq yp(u, v, t) - yq(u, v, t) \\ &\leq \sqrt{2} \cdot Smax(u, v) \cdot d(u, v) \end{aligned} \quad (6.14)$$

Source limits

To limit the apparent power flowing through the source, the following constraints are added. They correspond to the Constraints (3.37) and (3.38).

$$\forall t, \forall u \in N_{src}:$$

$$-Smax(u) \leq yps(u, t) \leq Smax(u) \quad (6.15)$$

$$-Smax(u) \leq yqs(u, t) \leq Smax(u) \quad (6.16)$$

The same approximations that are done in Constraints (3.23) and (3.24) are taken in account in case of the dynamic MIQP with one binary variable per edge.

$$\begin{aligned} -\sqrt{2} \cdot Smax(u, v) &\leq yps(u, t) + yqs(u, t) \\ &\leq \sqrt{2} \cdot Smax(u) \end{aligned} \quad (6.17)$$

$$\begin{aligned} -\sqrt{2} \cdot Smax(u) &\leq yps(u, t) - yqs(u, t) \\ &\leq \sqrt{2} \cdot Smax(u) \end{aligned} \quad (6.18)$$

Power balance constraints

The power balance constraints correspond to the Constraints (3.39), (3.40), (3.41) and (3.42). $\forall t, \forall u \in N \setminus N_{src}$:

$$\sum_{v \in N^{in}(u)} yp(v, u, t) - \sum_{v \in N^{out}(u)} yp(u, v, t) = P_{eq}(u, t) \quad (6.19)$$

$$\sum_{v \in N^{in}(u)} yq(v, u, t) - \sum_{v \in N^{out}(u)} yq(u, v, t) = Q_{eq}(u, t) \quad (6.20)$$

$$\forall t, \forall u \in N_{src}:$$

$$yps(u, t) + \sum_{v \in N^{in}(u)} yp(v, u, t) - \sum_{v \in N^{out}(u)} yp(u, v, t) = 0 \quad (6.21)$$

$$yqs(u, t) + \sum_{v \in N^{in}(u)} yq(v, u, t) - \sum_{v \in N^{out}(u)} yq(u, v, t) = 0 \quad (6.22)$$

6.2.2 Free Multiple Reconfigurations model

In this section, the Free Multiple Reconfigurations model is presented. It is applied on the MIQP with one binary variable per edge. The time t is integrated in its constraints. In fact, there are several loads and generations, and therefore several power flows (one per time unit considered).

In this case, The same constraints of the Fixed Reconfiguration case are applied with taking in account of the time t in the binary variables d .

Radiality constraints

The following constraints impose the radiality of the solution. This is the case named *Free Multiple Reconfigurations* where the configuration can change at each time t . For each time t :

$$\sum_{(u,v) \in A} d(u,v,t) = n_{bus} - n_{src} \quad (6.23)$$

Where $d(u,v,t)$ is a binary variable representing the state of the arc (u,v) at time t (1 if closed, 0 if opened).

As in the Chapter 3, Section 3.6, the fictitious flow should be added. The following constraints correspond to Constraints (3.26), (3.27) and (3.28)

$\forall t, \forall u \in N \setminus N_{src} :$

$$\sum_{v \in N^{in}(u)} f(v,u,t) - \sum_{v \in N^{out}(u)} f(u,v,t) = f_{eq}(u,t) \quad (6.24)$$

$\forall t, \forall u \in N_{src} :$

$$yfs(u,t) + \sum_{v \in N^{in}(u)} f(v,u,t) - \sum_{v \in N^{out}(u)} f(u,v,t) = f_{eq}(u,t) \quad (6.25)$$

$$\forall u \in N_{src} \cup \forall u, P_{eq}(u) > 0 : f_{eq}(u) = 0$$

$$\forall u \in N_{src} \cup \forall u, P_{eq}(u) < 0 : f_{eq}(u) = 1$$

For each branch (u,v) and $\forall t$:

$$-f_{max}(t) \cdot d(u,v,t) \leq f(u,v,t) \leq f_{max}(t) \cdot d(u,v,t) \quad (6.26)$$

$$f_{max} = \sum_{\forall u \in N} f_{eq}(u,t) \quad (6.27)$$

Voltage variation constraints

The time t is integrated for the same constraints in the Chapter 3, Section 3.6. The following constraints correspond to Constraints (3.29), (3.30), (3.31) and (3.32).

$\forall t, \forall (u,v) \in A :$

$$Us_{min} \cdot d(u,v,t) \leq yUs(u,v,u,t) \leq Us_{max} \cdot d(u,v,t) \quad (6.28)$$

$$Us_{min} \cdot d(u,v,t) \leq yUs(u,v,v,t) \leq Us_{max} \cdot d(u,v,t) \quad (6.29)$$

$$\begin{aligned} Us_{min}(1 - d(u,v,t)) &\leq Us(u,t) - yUs(u,v,u,t) \\ &\leq Us_{max}(1 - d(u,v,t)) \end{aligned} \quad (6.30)$$

$$\begin{aligned}
Us_{min}(1 - d(u, v, t)) &\leq Us(v, t) - yUs(u, v, v, t) \\
&\leq Us_{max}(1 - d(u, v, t))
\end{aligned} \tag{6.31}$$

The following constraints correspond to the Constraints (3.33) and (3.34). $\forall t, \forall u \in N_{src}$:

$$Us(u, t) = U_N^2 \tag{6.32}$$

$$\begin{aligned}
&\sum_{v \in N^{out}(u)} (yUs(u, v, u, t) - yUs(u, v, v, t)) \\
&+ \sum_{v \in N^{in}(u)} (yUs(v, u, u, t) - yUs(v, u, v, t)) \\
&= 2 \left(\sum_{v \in N^{out}(u)} R(u, v) \cdot yp(u, v, t) + X(u, v) \cdot yq(u, v, t) \right. \\
&\quad \left. - \sum_{v \in N^{in}(u)} R(v, u) \cdot yp(v, u, t) + X(v, u) \cdot yq(v, u, t) \right)
\end{aligned} \tag{6.33}$$

Branch limit

From Chapter 3, Section 3.6, the following constraints correspond to (3.35) and (3.36).

$\forall t, \forall (u, v) \in A$:

$$\begin{aligned}
-Smax(u, v) \cdot d(u, v, t) &\leq yp(u, v, t) \\
&\leq d(u, v, t) \cdot Smax(u, v)
\end{aligned} \tag{6.34}$$

$$\begin{aligned}
-Smax(u, v) \cdot d(u, v, t) &\leq yq(u, v, t) \\
&\leq d(u, v, t) \cdot Smax(u, v)
\end{aligned} \tag{6.35}$$

$$\begin{aligned}
-\sqrt{2} \cdot Smax(u, v) \cdot d(u, v, t) &\leq yp(u, v, t) + yq(u, v, t) \\
&\leq \sqrt{2} \cdot Smax(u, v) \cdot d(u, v, t)
\end{aligned} \tag{6.36}$$

$$\begin{aligned}
-\sqrt{2} \cdot Smax(u, v) \cdot d(u, v, t) &\leq yp(u, v, t) - yq(u, v, t) \\
&\leq \sqrt{2} \cdot Smax(u, v) \cdot d(u, v, t)
\end{aligned} \tag{6.37}$$

Source limits

To limit the apparent power flowing through the source, the following constraints are added. They correspond to the Constraints (3.37) and (3.38).

$\forall t, \forall u \in N_{src}$:

$$-Smax(u) \leq yps(u, t) \leq Smax(u) \tag{6.38}$$

$$-Smax(u) \leq yqs(u, t) \leq Smax(u) \tag{6.39}$$

The same approximations that are done in Constraints (3.23) and (3.24) are taken in account in case of the dynamic MIQP with one binary variable per edge.

$$\begin{aligned} -\sqrt{2} \cdot Smax(u, v) &\leq yps(u, t) + yqs(u, t) \\ &\leq \sqrt{2} \cdot Smax(u) \end{aligned} \quad (6.40)$$

$$\begin{aligned} -\sqrt{2} \cdot Smax(u) &\leq yps(u, t) - yqs(u, t) \\ &\leq \sqrt{2} \cdot Smax(u) \end{aligned} \quad (6.41)$$

Power balance constraints

The power balance constraints correspond to the Constraints (3.39), (3.40), (3.41) and (3.42). $\forall t, \forall u \in N \setminus N_{src}$:

$$\sum_{v \in N^{in}(u)} yp(v, u, t) - \sum_{v \in N^{out}(u)} yp(u, v, t) = P_{eq}(u, t) \quad (6.42)$$

$$\sum_{v \in N^{in}(u)} yq(v, u, t) - \sum_{v \in N^{out}(u)} yq(u, v, t) = Q_{eq}(u, t) \quad (6.43)$$

$\forall t, \forall u \in N_{src}$:

$$yps(u, t) + \sum_{v \in N^{in}(u)} yp(v, u, t) - \sum_{v \in N^{out}(u)} yp(u, v, t) = 0 \quad (6.44)$$

$$yqs(u, t) + \sum_{v \in N^{in}(u)} yq(v, u, t) - \sum_{v \in N^{out}(u)} yq(u, v, t) = 0 \quad (6.45)$$

6.2.3 Objective function

The objective function is as follows. It is applied for the Fixed Reconfiguration case. The voltage profile is maintained as the nominal voltage on all the network.

$$\begin{aligned} \min Z = & \frac{1}{U_N^2} \sum_{t \in T} \sum_{(u,v) \in A} R(u, v) (yp(u, v, t)^2 \\ & + yq(u, v, t)^2) \end{aligned} \quad (6.46)$$

This objective function is the amount of power losses in Megawatt (MW). The cost of power losses is not taken in account. Moreover, the cost of the control switches is not taken in account either. The next section consists of the introduction of the cost of control of switches which is useful in the case of Free Mutiple Reconfigurations. Moreover, the multiple reconfiguration with operational constraints is presented.

6.3 Accounting for the switching cost

The objective function (6.46) chooses the feasible configuration that minimizes the MW losses. However, from an industrial point of view, Megawatt-hour (MWh) losses have a cost in euros. Additionally, changing the configuration (switching the switches) incurs a cost that can be evaluated in euros. Some switches require manual operation, necessitating the dispatch of an operator, which generates a cost. Others, which are automatic, have their lifespan reduced with each change of state. Each switch state change therefore generates a cost, depending on its type. An economic objective function should, therefore, consider not only the losses over time but also the cost of changing the configuration relative to the current configuration (initial configuration). Thus, a switch that is expensive to change will only be switched if the time interval during which it reduces losses is large enough to justify the cost of changing it.

The following constraints are set to include the cost of control of switches in the objective function. For each arc (u, v) , let $y_\Delta(u, v, t) \in [0, 1]$ be a continuous variable of control of the switch (u, v) for each time t . $y_\Delta(u, v, t)$ is null if (u, v) is a non-controllable branch.

For the time $T = 0$, we want to know if an arc (u, v) has changed his state from 1 to 0 (ON to OFF) or for 0 to 1 (OFF to ON). So, if it is true, the variable $d(u, v, 0)$ and the initial state $is(u, v)$ must be different. Therefore, the difference must be equal to 1 if there is a change in state, otherwise it must be 0. The difference is represented by the variable $y_\Delta(u, v) = (d(u, v, 0) - is(u, v))^2$. We have added the power in order to keep the positivity of the result and to count it to add it to the objective function. The power does not affect the result, since the result is binary (1 or 0). Therefore, $y_\Delta(u, v) = (d(u, v, 0) - is(u, v))^2 = d(u, v, 0)^2 + is(u, v)^2 - 2 \cdot d(u, v, 0) \cdot is(u, v) = d(u, v, 0) \cdot (1 - 2 \cdot is(u, v)) + is(u, v)$. If this variable is one, then the configuration requires a change of the state of the switch (u, v) .

The last equality is valid since we have $d(u, v, 0)^2 = d(u, v, 0)$ and $is(u, v)^2 = is(u, v)$ ($d(u, v, 0)$ and $is(u, v)$ are binary). Therefore, we obtain the constraint (6.47) which is linear.

Let $T = \{0, \dots, n_t - 1\}$ be the set of considered time instants. Let n_t be the size of T . We have the following set of constraints.

$\forall$ controllable $(u, v) \in A$:

$$y_\Delta(u, v, 0) = d(u, v, 0) \cdot (1 - 2 \cdot is(u, v)) + is(u, v) \quad (6.47)$$

$is(u, v)$ is the initial state of the arc (u, v) . The constraint (6.47) is the expansion of $(d(u, v, 0) - is(u, v))^2$, to detect if the arc (u, v) changes its state at time $T = 0$.

We want to count the change between the time $t - 1$ and time t . The variable y_Δ counts the amount of change, which is 1 if there is a different value between $d(u, v, t - 1)$ and $d(u, v, t)$ or 0 if there is no change ($d(u, v, t - 1) = d(u, v, t)$). We suppose that $y_\Delta(u, v, t) = |d(u, v, t - 1) - d(u, v, t)|$. One could have say that we could make $y_\Delta(u, v, t) = (d(u, v, t - 1) - d(u, v, t))^2$ like in the case between the initial state and $T = 0$. This is

not valid, because $is(u, v)$ is a data and not a variable. So, we will obtain a non linear constraint.

To linearize $|d(u, v, t - 1) - d(u, v, t)|$, we add the constraints (6.48) and (6.49). To prove that this linearization is valid, we will treat the following case. If the arc (u, v) does not change its state between $t - 1$ and t , therefore by (6.48) and (6.49), we have $y_\Delta(u, v, t) \geq 0$. Due to the presence of y_Δ in the objective function, the solver will take the minimum value of y_Δ that respects its domain ($y_\Delta \in [0, 1]$). Therefore, the solver will choose $y_\Delta(u, v, t) = 0$.

$$\forall t \in T \setminus \{0\}, \forall \text{ controllable } (u, v) \in A:$$

$$y_\Delta(u, v, t) \geq d(u, v, t) - d(u, v, t - 1) \quad (6.48)$$

$$y_\Delta(u, v, t) \geq -(d(u, v, t) - d(u, v, t - 1)) \quad (6.49)$$

Constraints (6.48) and (6.49) are the linearization of the absolute value of $(d(u, v, t) - d(u, v, t - 1))$ that appears in the objective function, in order to count the number of control of switches at each time.

For the other cases, the arc (u, v) changes its state between $t - 1$ and t . Therefore, we will have by constraints (6.48) and (6.49) that $y_\Delta(u, v, t) \geq 1$ and $y_\Delta(u, v, t) \geq -1$. Therefore, $y_\Delta(u, v, t) \geq 1$ and $y_\Delta(u, v, t) = 1$ because $y_\Delta(u, v, t) \in [0, 1]$. So, as a conclusion, the variable y_Δ will count the number of changes between two subsequent instants in T .

The objective function is as follows. It replace the one in Section 6.2.3. C_{loss} is the cost of losses in MWh. $C_m(u, v)$ is the control cost of the manual or automatic switch (u, v) .

$$\begin{aligned} \min Z = & \frac{1}{U_N^2} \sum_{t \in T} C_{loss} \cdot (\sum_{(u,v) \in A} R(u, v)(yp(u, v, t)^2 \\ & + yq(u, v, t)^2) + \sum_{\text{controllable}(u,v)} C_m(u, v) \cdot y_\Delta(u, v, t)) \end{aligned} \quad (6.50)$$

6.3.1 Multiple reconfigurations with operational constraints

As mentioned in the introduction, imposing a ψ_{max} limit on the number of configurations has its advantages, as changing it instantly (at each time) presents technological and economic barriers. We have treated the case where only one time configuration's change is allowed by only keeping the radiality constraint as it is in (3.25) without the introduction of the time t . For more than one configuration allowed, this case is called the multiple reconfigurations with operational constraints with ψ_{max} = number of configurations. It consists of the Free Mutiple Reconfigurations constraint's model with additional constraints to impose a maximum number of reconfigurations on a set of time T .

For the case of multiple configurations with a value for $\psi_{max} \geq 1$, a continuous variable $\alpha(u, v, t) \in [-1, 1]$ is introduced for each time t and on each controllable arc (switch) (u, v) . Additionally, a continuous variable $\psi(t) \in [0, 1]$ is defined for each time t . The

following constraints are implemented to limit the number of output configurations over the designated time interval set $T = \{0, \dots, n_t - 1\}$.

$$\forall t \in T \setminus \{n_t - 1\}, \forall (u, v) \in A:$$

$$-\psi(t) \leq \alpha(u, v, t) \leq \psi(t) \quad (6.51)$$

$$d(u, v, 0) = is(u, v) + \alpha(u, v, 0) \quad (6.52)$$

$$d(u, v, t + 1) = d(u, v, t) + \alpha(u, v, t + 1) \quad (6.53)$$

$$\sum_{t \in T} \psi(t) \leq \psi_{max} \quad (6.54)$$

Where ψ_{max} is the maximum number of configurations. From constraints (6.52) and (6.53), $\alpha(u, v, t) \in \{-1, 0, 1\}$ for all t and (u, v) due to the fact that $\alpha(u, v, t)$ depends from $d(u, v, t)$ and $d(u, v, t + 1)$ which are binary variables. If $\alpha(u, v, t) = 1$, so there is an arc (u, v) that has changed its state between $t - 1$ and t . By constraint (6.51), $-\psi(t) \leq 1 \leq \psi(t)$ with respect to $\psi(t) \in [0, 1]$. Therefore, $\psi(t) = 1$ and the topology is changed between $t - 1$ and t . By constraint (6.54), the number of changes of the topologies is limited to ψ_{max} . The same goes if $\alpha(u, v, t) = 0$ and $\alpha(u, v, t) = -1$ and in all cases, $\psi(t)$ will take values in $\{0, 1\}$, which determines if there is a change of topology at time t .

6.4 Experiments

In this section, the performance of the dynamic MIQP with one binary variable per edge is tested on a modified IEEE-33 test system. The solver used is Gurobi Optimizer version 10.0.1 with a modified parameter : MIPGap set to 0, on a computer that has an Intel(R) Core(TM) i5-9500 CPU @ 3.00GHz with 32 GB of RAM.

The modified IEEE-33 bus under study is referenced in [BW89]. The coefficients for hourly load (k_{load}) and generation (k_{gen}) are presented in Table 6.1. The selected value for the reactive power ($\tan(\phi)$) is 0.2. The simulation results for various scenarios on the modified IEEE-33 bus are shown in Table 6.2 and Table 6.3. In the cases involving the Multiple Reconfigurations, a time limit of 350 seconds is imposed, while the case with a Fixed Reconfiguration has no time limit for the simulation. The number of manipulations represents the total number of changes of the state of each switch on $T = \{0, \dots, 11\}$. The switch manipulation cost is selected arbitrarily. C_{loss} equals 200 EUR/MWh and C_m is 10 EUR.

Table 6.1: Active power load and generation coefficient

Time (h)	k_{load}	k_{gen}	Time (h)	k_{load}	k_{gen}
1	0.9	0.12	7	0.8	0.8
2	0.9	0.28	8	0.8	0.68
3	0.9	0.48	9	0.8	0.52
4	0.9	0.48	10	0.7	0.52
5	0.9	0.36	11	0.8	0.4
6	0.8	0.48	12	0.8	0.24

It is expected that the case without a limitation on the number of configurations (Free Multiple Reconfigurations) yields the most favorable outcome compared to the case where a limit on the number of configurations is imposed (as indicated by the presence of ψ_{max}) in terms of power losses. However, this is not observed in this study (Table 6.2). The result is unexpected since, with a fixed time limit, the case with a limited number of configurations performs better than the one without limitations ($289.905 \geq 289.806$ in terms of objective function between the free multiple reconfiguration case and the multiple reconfigurations with operational constraints) due to the fixed time limit of the solver.

Moreover, focusing solely on the cases with a limit on the number of configurations ($\psi_{max} = 2,3$), it is observed that the case with $\psi_{max} = 2$ and $\psi_{max} = 3$ have the same performance in terms of total power losses and number of manipulations of switches. It means that these two cases have the same topology since they have the same total of power losses. This observation aligns with the logical expectation that increasing the value of ψ_{max} would provide a same or greater opportunity for achieving improved results in terms of power losses and number of manipulations of switches. It is worth to say that the topology in these two cases ($\psi_{max} = 2,3$) changes at time $t = 2h$ and $t = 3h$ ($\psi(t) = 1$ for $t \in \{2, 3\}$, 0 for $t \in T \setminus \{2, 3\}$). Thus, the two cases conserve the initial topology.

Table 6.2: Results of the objective function and total cost for the different cases on a modified IEEE-33 bus

	Obj. function	Total cost (Eur)
Fixed Reconfiguration	294.999	330.723
Free Multiple Reconfigurations	289.905	325.827
Multiple Reconfigurations $\psi_{max} = 2$	289.806	322.793
Multiple Reconfigurations $\psi_{max} = 3$	289.806	322.793

Table 6.3: The number of manipulations and simulation's time for the different cases on a modified IEEE-33 bus

	Number of manip.	Time (sec.)
Fixed Reconfiguration	6	11.25
Free Multiple Reconfigurations	6	350
Multiple Reconfigurations $\psi_{max} = 2$	6	350
Multiple Reconfigurations $\psi_{max} = 3$	6	350

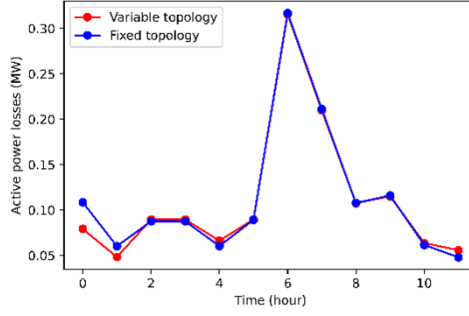


Figure 6.2: Active power losses at each hour for fixed and free multiple reconfiguration

In Fig. 6.2, a comparison is made between the case of Fixed Reconfiguration (involving a single configuration change) and the case of Free multiple reconfiguration (variable topology). The simulation for the former is conducted without a time limit, whereas the latter is subjected to a time limit of 350 seconds. It is evident that the second case consistently exhibits better results in terms of active power losses at most of hours, which aligns with expectations ($289.905 \leq 294.999$ from Table 6.2).

It is worth saying that the Free Multiple Reconfiguration case was tested on the agency [Kar]. The solver's computation time was 845780 sec. for a solution of 0.74% of a gap from the optimal solution. Therefore, for a large network, Free Multiple Reconfiguration is not the best option to consider in load-curve-based optimization.

6.5 Single Reconfiguration versus Fixed Reconfiguration

As we have seen in the results, the Free Multiple Reconfigurations is not desirable due to the solver's large computational time on a modified IEEE-33 system. The Fixed Reconfiguration is the best choice because of its acceptable computational time (11.25 seconds for the modified IEEE-33).

In this section, the Single Reconfiguration case is compared to the Fixed Reconfiguration. The goal is to determine whether the Fixed Reconfiguration offers advantages over the Single Reconfiguration. DSOs can use the Single Reconfiguration with representative operating points corresponding to an entire period of the year (e.g., summer or winter). This approach benefits from faster computational times. On the other hand, the Fixed Reconfiguration benefits from the ability to accommodate variations in loads and generations. The feasible configuration provided by the solver will satisfy the constraints across all these variations, resulting in the best feasible configuration with the lowest power losses.

To apply load-curve optimization to the SRD network and achieve optimal results for the solver's computational time, the network used in these comparisons is the simplified version obtained in Chapter 5. It consists of an agency of the SRD network applied to the low-impact switch elimination methods. Recall that this network contains 33 switches (reduced from 403 switches before applying the low-impact switch elimination method).

6.5.1 Single Reconfiguration case

For the single reconfiguration, the operating points chosen $OP_i = (k_{load}, k_{gen})$ are $OP_1 = (0.075, 0.2)$ and $OP_2 = (0.45, 0.1)$. OP_1 and OP_2 are coefficients for each the load and generation applied to all vertices of the network where OP_1 represents a low load, high generation and high load, low generation for OP_2 respectively. The MIQP with one binary variable per edge presented in the Chapter 3, Section 3.6 is launched sequentially on each OP_1 and OP_2 . Due to the fact that in this comparison, we will be able to change the configuration only once among the set of times, the switches cost therefore will not be taken in the objective function. Only the power losses are considered. The optimal solution for these two operating point are presented in Fig. 6.3, Fig. 6.4 and table 5.4. The configuration of the switches are presented in 6.3.

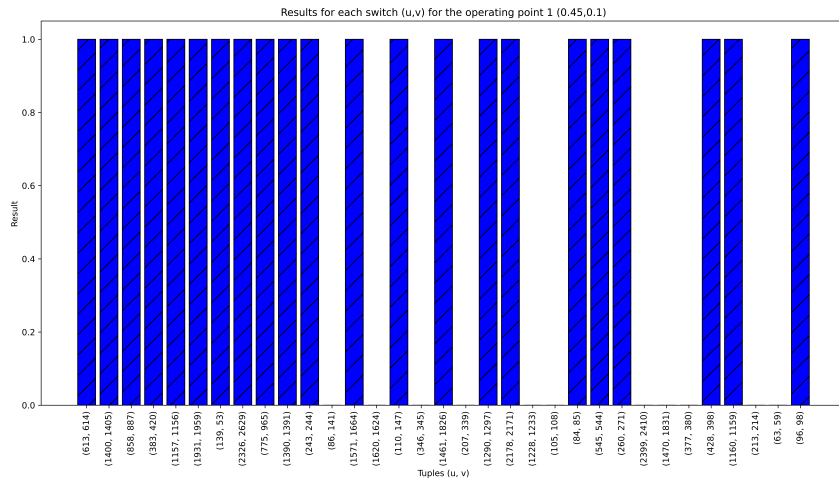


Figure 6.3: Results for each switch (u, v) for OP_1

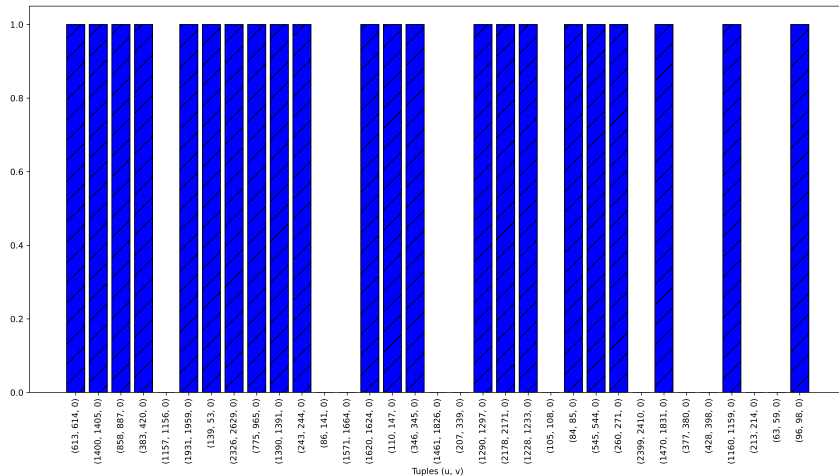


Figure 6.4: Results for each switch (u, v) for OP_2

As we can see, the optimal solutions for OP_1 and OP_2 do not present the same feasible configuration for both OP_1 and OP_2 . Therefore, comparing this with the dynamic

case with a fixed configuration becomes interesting to identify the best solution (feasible configuration) among a set of operating points where the optimal one differs for two or more operating points in this set.

Table 6.4: Results of simulations on the simplified network for OP_1 and OP_2

	OP_1	OP_2
Initial power loss (kW)	0.881	0.028
Obj. function (kW)	0.794	0.025
Time (sec.)	2.10	14.17
Final power loss (kW)	0.69	0.023
Delta loss (%) (MW)	- 20	- 17.71

From Table 6.4, the initial power loss refers to the amount of power loss in the initial configuration, as determined by the power flow simulation using Pandapower for both OP_1 and OP_2 . The final power loss is the amount of power loss in the feasible configuration (the optimal solution provided by the solver), also determined by the power flow simulation using Pandapower. The results demonstrate a reduction in power loss for both operating points.

Now, we will consider a set of operating points that includes these two operating points, ensuring that there is a distinct optimal feasible configuration for each case, and examine the Fixed Reconfiguration case in comparison to the Single Reconfiguration case in terms of its advantages.

6.5.2 The Fixed Reconfiguration case

We suppose a set of operating points including OP_1 and OP_2 which are supposed to be critical points as we said in the previous section. The set is presented in Fig. 6.5.2.

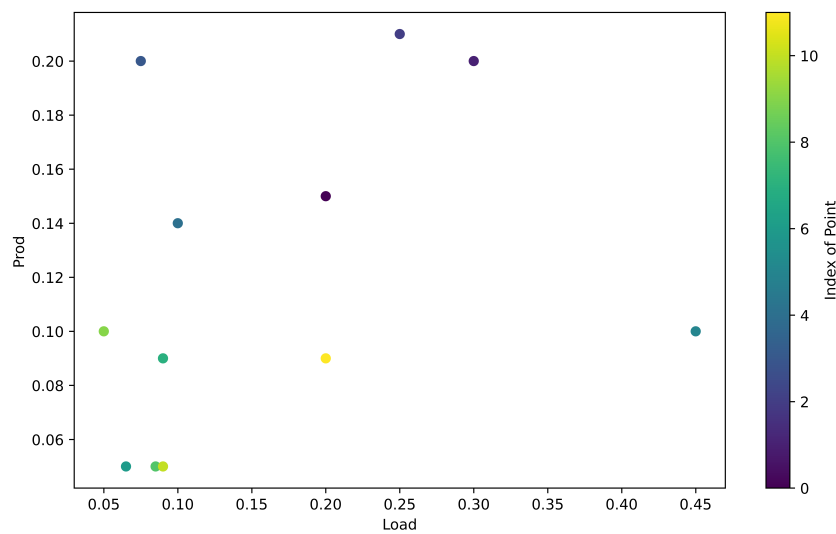


Figure 6.5: The set of operating points ($load, prod$)

The MIQP in Section 6.2.1 is applied on the set of operating points in Fig. 6.5.2. A unique feasible configuration will be obtained for all the set of operating points.

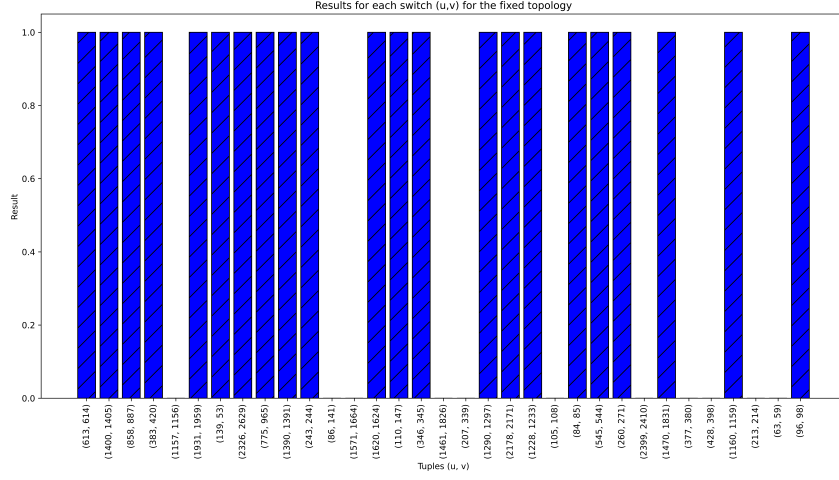


Figure 6.6: Solution of the switches in the Fixed Reconfiguration case

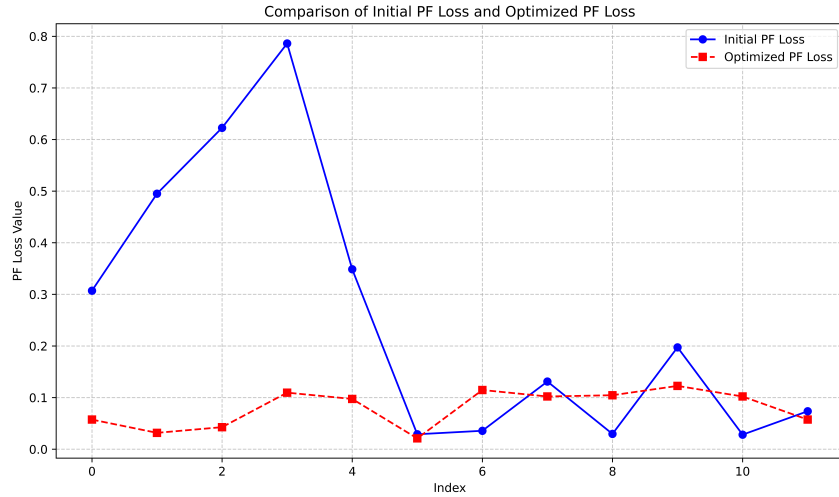


Figure 6.7: Comparison between initial PF loss and optimized PF loss

The OP_1 and OP_2 are at times $T = 5$ and $T = 3$, respectively. The feasible configuration of the switches in this simulation is presented in Fig. 6.5.2. The solver's computational time is 182 seconds. The total reduction in power loss is 68.7% between the initial configuration and the feasible configuration.

In comparison with Fig. 6.4, we can conclude that the feasible configuration in the case of a Fixed Reconfiguration is the same as the Single Reconfiguration case with OP_2 as the reference point. Therefore, the feasible configuration in the Fixed Reconfiguration case will present the minimal amount of power loss at time $T = 3$, while for other times, it cannot be guaranteed that the power loss will be minimized or reduced. This is particularly true for $T = 5$, where, in the Single Reconfiguration case, the feasible configuration

for OP_1 is different from the one for OP_2 . The solver chooses the configuration that provides the best reduction.

As shown in Fig. 6.5.2, the blue line represents the power loss for the initial configuration. The red line shows the power loss for the feasible configuration in the MIQP with the Fixed Reconfiguration case. For the set of times $T = \{0, 1, 2, 3, 4\}$, there is a significant reduction in power loss compared to the initial configuration for each time. This is due to the fact that the feasible configuration found by the solver in the Fixed Reconfiguration case for these operating points is the same as the Single Reconfiguration with OP_2 . However, this feasible configuration is not optimal for the set of times $T = \{5, 6, 8, 10\}$. The solver adopts the feasible configuration for $T = 3$ because it presents the highest initial power loss compared to the other times (0.79 kW). The advantage is that this feasible configuration respects the constraints for the set $T = \{5, 6, 8, 10\}$, even though it is not the optimal configuration.

Thus, an advantage of the Fixed Reconfiguration compared to the Single Reconfiguration case is that it can account for load and generation curves while providing a feasible configuration that meets the constraints for all operating points and is optimal for specific operating points.

Now, we propose introducing a weighted timing approach into the objective function to emphasize the importance of the times that do not show an improvement in terms of final power loss.

6.5.3 Weighted Fixed Reconfiguration

The weighted timing approach becomes important when all time periods do not have the same importance or the same requirements. By assigning a weight to each time point, this method allows to highlight critical or costly moments while giving less importance to periods of low impact. This introduces flexibility to optimize resources or performances according to the importance of events, thus being halfway between a deterministic (temporal) approach and a probabilistic (stochastic) approach.

In this section, we will present what is a weighted objective function in the Fixed Reconfiguration model. In this context, a weight corresponds to the relative importance of the different variables or components of the objective function. Suppose that we want to include a weight $w(t)$ for each time $t \in T$. The weighted objective function is defined as follows.

$$\min Z = \frac{1}{U_N^2} \sum_{t \in T} w(t) \sum_{(u,v) \in A} R(u,v) (yp(u,v,t)^2 + yq(u,v,t)^2) \quad (6.55)$$

Now, let $w = [0.5, 0.5, 0.5, 0.5, 0.5, 20, 0.5, 0.5, 5, 0.5, 5, 5]$ be the weight applied to the objective function for each time t . This chosen weight gives more emphasis to the times where power losses have not been improved in the feasible configuration of the fixed topology studied in the previous subsection. For example, a weight of 20 has been chosen for time $T = 5$, where, as shown in Fig. 6.5.2, the initial power losses for the Fixed Reconfiguration case are almost the same as those in the feasible configuration obtained

by the solver (0.02 MW). Similarly, weights of 5 are applied for times $T = \{8, 10, 11\}$ to encourage the reduction of losses (improvement) in the feasible configuration chosen by the solver. The feasible configuration yields the following solution for each switch.

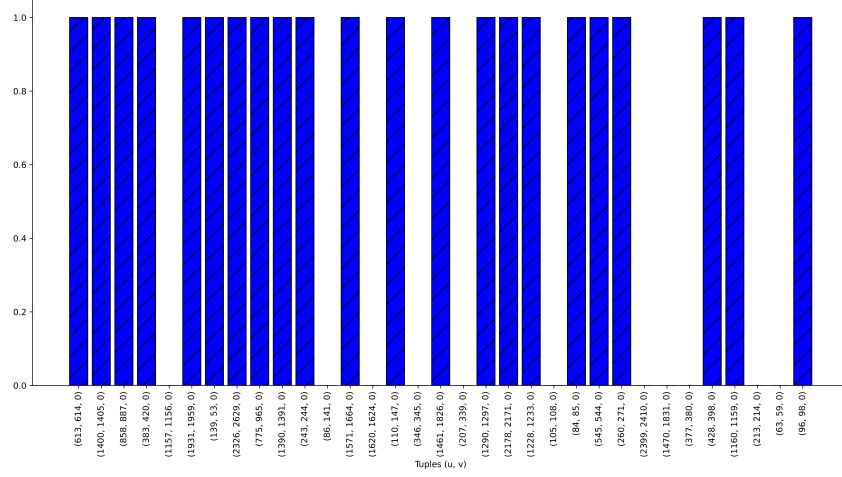


Figure 6.8: Solution of the switches in the weighted Fixed Reconfiguration case

The computational time is 194.55 seconds. The value of the objective function is 2.23. The relative loss reduction is 68.8 %.

From Fig. 6.5.3, the feasible configuration provided by the solver differs from that of the Fixed Reconfiguration case (Fig. 6.5.2) and from the one given in the Single Reconfiguration for the two operating points OP_1 and OP_2 (Figs. 6.3 and 6.4). This indicates that the solver has selected a feasible configuration that is suitable for the weighted times. Specifically, as mentioned, the chosen operating points represent two critical points, OP_1 and OP_2 . When considering the set of timings in the weighted fixed configuration case, this set allows for more than three possible feasible configurations. The addition of weights in the objective function influences the decision of which feasible configuration to select. Therefore, choosing the appropriate weight can aid in selecting the optimal feasible configuration.

6.6 Conclusion

In this chapter, a study on load and generation curve-based optimization for the Distribution Network Reconfiguration (DNR) problem is presented. A generalization of the Single Reconfiguration, applied in previous contributions to reduce the solver's computational time, is extended to the context of a set of window instants. The Fixed Reconfiguration case, where the goal is to have only one reconfiguration among a set of times, and the free multiple reconfiguration case, where the solver can change the feasible configuration at each time instant, are examined. A limitation on the maximum number of obtained feasible configurations, named multiple reconfigurations with operational constraints, is also presented. A comparison between the Free Multiple Reconfigurations and multiple reconfigurations with operational constraints is tested on a modified IEEE-33 bus network under various load and generation scenarios for each hour.

On the other hand, a comparison between the Single Reconfiguration case and the Fixed Reconfiguration case is presented to understand the advantages of each. The comparison is made on the simplified network obtained in Chapter 5. The Fixed Reconfiguration allows us to obtain a feasible configuration that respects the constraints for all operating points and is optimal for a specific one. Here, the concept of the weighted Fixed Reconfiguration case is introduced, where the goal is to give importance to the set of times that do not show improvement in terms of final power losses. This approach allows Distribution System Operators (DSOs) to adjust the weights according to the times that need a better feasible configuration.

Now, another constraint appears to be crucial, where the case of exceeded power generation (decentralized generation) is presented. The question is, what if the solver is unable to find a feasible configuration that respects all the constraints for all times? The exceeded amount of generation can be a barrier for load curve-based optimization. The next chapter will provide a way to address this case.

Chapter 7

Distributed Generations Curtailment for Maintaining Voltage Stabilization

The progressive integration of distributed generation (DG) gives rise to significant over-generations within distribution networks. In some cases, it may lead to grid instability and voltage fluctuations, resulting in equipment damage or failures.

The goal of this chapter is to mitigate the impacts of high integrations of distributed generations, such as grid instability and voltage stabilization challenges in case of load-curve based optimization for the Distribution Network Reconfiguration (DNR) problem.

In the context of this thesis, we have seen that the high integration of distributed generation in distribution networks can lead to barriers in finding a feasible configuration, especially in the case of load-curve-based optimization for the Distribution Network Reconfiguration (DNR) problem. In this chapter, we will discuss this constraint and explore solutions.

7.1 Introduction

Distribution Network Reconfiguration (DNR) is a method to optimize the electrical network in terms of power losses while maintaining the required voltage. Relaxing the voltage profiles is needed to allow more flexibility in the power system.

In the context of this thesis, we have seen DNR as a way to minimize power losses. A Single Reconfiguration can be made for a single operating point consisting of a tuple $(load, prod)$. In the previous chapter, a generalization was made, and load-curve-based optimization for the DNR problem was implemented.

In this context, the Fixed Reconfiguration case is interesting to discuss and study in comparison to the Single Reconfiguration case (a single operating point) due to its capacity to take into account multiple time windows while providing a feasible configuration that respects the electrical and operational constraints for each instant but is optimal for one specific time. Moreover, its acceptable solver's computational time to find the feasible configuration makes it more attractive.

In this chapter, we will continue with load-curve-based optimization for the DNR problem, specifically with the Fixed Reconfiguration case, to discuss and find a solution for the high integration of decentralized generation, where finding a feasible configuration is difficult or impossible. Power curtailment can be employed for two possible uses: load-curve optimization in line with Chapter 6, and sizing the network when installing new infrastructure required for the integration of a decentralized producer.

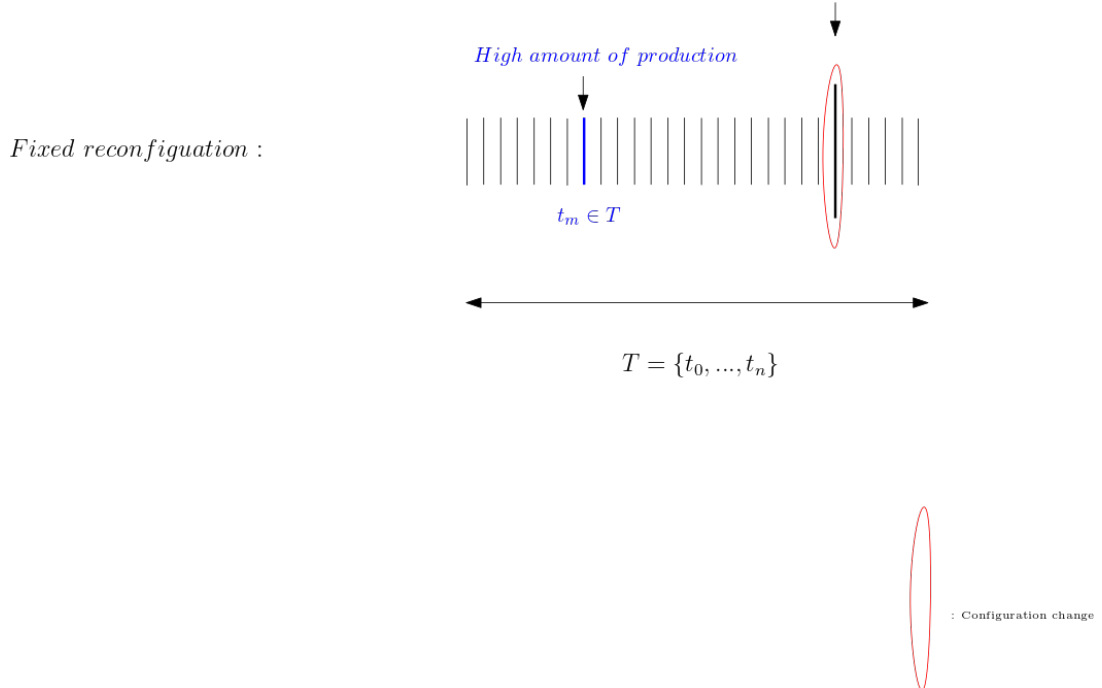


Figure 7.1: Fixed Reconfiguration case with a high amount of power generation

7.1.1 Literature Review

In the existing literature, various methods for preventing the impact of high integrations of production have been proposed. In [HSB21], a discussion addresses the different impact and solutions to overcome the high integration of high photovoltaic voltage in low voltage networks. In [Lei+17], a study of the problem of identifying critical switches in the process of dynamic DNR is presented. In [Kou+16], a novel approach for the online reconfiguration of active distribution networks is proposed to maximize the integration of power produced by DG units while minimizing power curtailment. It presents a multi-objective function that contains not only power losses, but curtailment and voltage. In [Rib+18], a case of study to discuss the impact of high integration of generations using voltage control simulations is presented.

This chapter proposes two models based on the Fixed Reconfiguration model presented in Chapter 6, Section 6.2.1. A single feasible configuration will be obtained for the set of time instants. The first proposed model involves the relaxation of voltage constraints curtailment. The second model is the power curtailment model, where the contribution lies in the linearization of the constraints that detect voltage violations and quantify the curtailed amount while imposing a maximum limit on curtailment occurrences. Both models lie in the context of solving the constraint of excess generation, as mentioned in the introduction. The effectiveness of this approach is evaluated using a small network and a modified version of the IEEE 33-bus test system.

7.2 Relaxation of the voltage constraints

The relaxation in voltage constraints makes it easier to find one feasible configuration that satisfies the network across all time instants with different conditions of load and generation without violating the voltage limits. Without such relaxation, optimization may require different configurations for different times to handle fluctuations, which means multiple reconfigurations. This suits our case where we are studying the Fixed Reconfiguration case in a load-based optimization using the DNR problem. Voltage relaxation enables a single configuration to cope with various situations, such as peak load or high decentralized generation, for instance, without voltage limits being exceeded.

For each time t and vertex u , let $\Delta(u, t) \in [0, 1]$ be a relaxation variable for the voltage variation.

The voltage squared at the non-source vertices is relaxed using the following constraint.

$$\begin{aligned}
& \sum_{v \in N^{out}(u)} (yUs(u, v, u, t) - yUs(u, v, v, t)) \\
& + \sum_{v \in N^{in}(u)} (yUs(v, u, u, t) - yUs(v, u, v, t)) + \Delta(u, t) \\
& = 2 \left(\sum_{v \in N^{out}(u)} R(u, v) \cdot yp(u, v, t) + X(u, v) \cdot yq(u, v, t) \right. \\
& \quad \left. - \sum_{v \in N^{in}(u)} R(v, u) \cdot yp(v, u, t) + X(v, u) \cdot yq(v, u, t) \right)
\end{aligned} \tag{7.1}$$

In (7.1), the goal of $\Delta(u, t)$ here is to relax the value of the sum $yUs(u, v, u, t) - yUs(u, v, v, t)$ or $yUs(v, u, u, t) - yUs(v, u, v, t)$ (which are the voltage drop on each vertex) depending if v is a direct predecessor or successor of u .

The variable $\Delta(u, t)$ for each source vertex u is fixed as null.

$\forall t, \forall u \in N_{src}$:

$$\Delta(u, t) = 0 \quad (7.2)$$

$$Us(u, t) = U_N^2 \quad (7.3)$$

$\forall t, \forall (u, v) \in A$:

$$\begin{aligned} Us_{min} \cdot d(u, v,) &\leq yUs(u, v, u, t) \\ &\leq Us_{max} \cdot d(u, v,) + \Delta(u, t) \end{aligned} \quad (7.4)$$

$$\begin{aligned} Us_{min} \cdot d(u, v,) &\leq yUs(u, v, v, t) \\ &\leq Us_{max} \cdot d(u, v,) + \Delta(u, t) \end{aligned} \quad (7.5)$$

$$\begin{aligned} Us_{min}(1 - d(u, v,)) &\leq Us(u, t) - yUs(u, v, u, t) \\ &\leq Us_{max}(1 - d(u, v,)) + \Delta(u, t) \end{aligned} \quad (7.6)$$

$$\begin{aligned} Us_{min}(1 - d(u, v,)) &\leq Us(v, t) - yUs(u, v, v, t) \\ &\leq Us_{max}(1 - d(u, v,)) + \Delta(u, t) \end{aligned} \quad (7.7)$$

In (7.4) and (7.5), the bounds of yUs of each arc are relaxed with Δ . Otherwise, the model will be infeasible if the voltage surpasses $Us_{max} = 1.1^2 * U_N^2$. Thus, it is crucial to relax the bounds of Us due to the fact that yUs is an intermediate variable that depends on Us (see (7.6) and (7.7)).

The linearization of the condition that if $yUs \geq Us_{max}$, then $\Delta = yUs - Us_{max}$ is as following:

$\forall t, \forall (u, v) \in A$:

$$\begin{aligned} -Us_{max} \cdot (1 - bin(u, t)) &\leq yUs(u, v, u, t) - Us_{max} \\ &\leq Us_{max} \cdot bin(u, t) \end{aligned} \quad (7.8)$$

$$\begin{aligned} yUs(u, v, u, t) - Us_{max} - Us_{max} \cdot (1 - bin(u, t)) &\leq \Delta(u, t) \\ &\leq Us_{max} \cdot bin(u, t) \end{aligned} \quad (7.9)$$

In (7.8) and (7.9), we ensure that for each arc (u, v) and t , for $u \in G$, if $yUs(u, v, u, t) \geq Us_{max}$, then $\Delta(u, t) = yUs(u, v, u, t) - Us_{max}$. Else, $\Delta(u, t) = 0$. The same goes for $v \in G$ for the same arc (u, v) and t . The linearization is done with the binary variable $bin(u)$ for each vertex u .

7.3 Power Curtailment model

In this section, the power curtailment model is presented. It is crucial to determine the amount of curtailed power that results from surpassing voltage limits. The concept behind this model is to relax the power balance constraints in Section 6.2.1. The goal

is to determine the amount of production curtailment required to comply with voltage limits in the case of high integration of distributed generation.

$$\begin{aligned} & \sum_{v \in N^{in}(u)} yp(v, u, t) - \sum_{v \in N^{out}(u)} yp(u, v, t) \\ & = P_{eq}(u, t) + curt(u, t) \end{aligned} \quad (7.10)$$

Where $curt(u, t) \in [0, 10]$ is a continuous variable for each u, t . In (7.10), $curt(u, t)$ tends to reduce the total value of production that causes the violation of voltage limits at each vertex u and time t . It is worth to mention that $P_{eq}(u, t)$ is negative in case of production.

$\forall t, \forall (u, v) \in A :$

$$\begin{aligned} & Us_{max} - 1000000 \cdot (1 - bin_{curt}(u, t)) \leq yUs(u, v, u, t) \\ & \leq Us_{max} + 1000000 \cdot (1 - bin_{curt}(u, t)) \end{aligned} \quad (7.11)$$

$\forall t :$

$$curt(u, t) \leq 10 \cdot bin_{curt}(u, t) \quad (7.12)$$

$bin_{curt}(u, t)$ is a binary variable for each vertex u and time t . In (7.11) and (7.12), the following condition is linearized: if yUs surpasses Us_{max} , then $bin_{curt} = 1$ and $curt$ will take values in $[0, 10]$. Else, $bin_{curt} = 0$ and $curt = 0$. Moreover, we can control the times of power curtailment among all points of time by controlling the number of the binary variable bin :

$$bin_{curt}(u, t) \leq M \quad (7.13)$$

Where M is the maximum number of power curtailment instances.

It is worth mentioning that, contrary to the literature, the objective function takes into account only the power losses without considering the cost of curtailment. In fact, the model that captures the loss in power within a curtailment scenario—omitting the cost associated with curtailed power—is vital for several reasons. This approach will be applied to simplify analyses to gain insight into the technical aspects of losses and their effects on efficiency and system reliability. It reduces energy wastage and increases the stability of the grid by optimizing system performance. Furthermore, it provides a baseline for benchmarking between alternative curtailment options and typically serves as a regulatory compliance requirement driven by the goal of reducing technical power loss.

7.4 Experiments

In this section, curtailment model and relaxation voltage model are tested. First, the curtailment model applied to the Fixed Reconfiguration model (Section 6.2.1) is tested on a small network with two distributed generations with fixed generations. Then, both models are tested on a IEEE-33 test system. This network is modified to remove loads and put generations. The solver used is Gurobi Optimizer version 10.0.1 with a modified

parameter : MIPGap set to 0, on a computer that has an Intel(R) Core(TM) i5-9500 CPU @ 3.00GHz with 32 GB of RAM.

For the small network, a distributed generation is placed on vertex 1 and 2 of 5 MW of active power Fig. 7.2. These values are expected to surpass the specified voltage limit set of +10% of the nominal voltage. The resistance on the branches is 3.535Ω with no reactance. The nominal voltage of the source of the network in the following example is 20 kV which is used to approximate the voltage in the objective function. The voltage of the source used to determine the voltage profile on each vertex is fixed to 1.03 p.u. The results are presented in the following table.

Table 7.1: Results of the small scale electrical network

	$V(1)$ (p.u)	$V(2)$ (p.u)	Power losses (MW)
Curtailment model	1.086	1.1	0.401
Power flow	1.083	1.096	0.36

The result of the optimization using the Curtailment model launched on the small network above presents a curtailed power of 3.289 MW on vertex 2. A power flow simulation was launched on the solution by taking into account the shaving of the exceeded power using Pandapower, an open-source Python library [Thu+18]. As shown in Table 7.1, the voltage values are lower than the results of the Curtailment model due to the approximations made on the voltage constraints to maintain them as linear constraints. Consequently, the Curtailment model ensures a peak shaving of the exceeded power that violates the voltage limits of vertex 2 while keeping vertex 1 without curtailment. The total active power on the source vertex is therefore **6.718 MW**. Thus, the maximum supported amount of energy by this network, while respecting the +10% voltage limit, is **6.718 MW**.

The IEEE-33 bus under study is referenced in [BW89]. The case tested is the Fixed Reconfiguration case, using the Fixed Reconfiguration model and where a generation curve $\{5, 5, 0.4\}$ is placed on the same buses. This generation curve presents exceeded generation on the first two points (5 MW). All other buses do not present loads, generation, or reactive power. The nominal voltage of the source of the network in the following example is 20 kV, which is used to approximate the voltage in the objective function. The voltage of the source used to determine the voltage profile on each vertex is fixed at 1.03 p.u. We remind that there will be one single feasible configuration solution for all time instants.

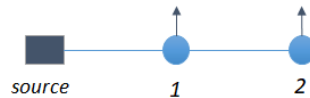


Figure 7.2: A small scale electrical network

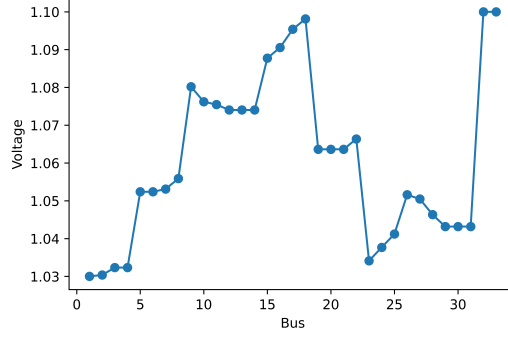


Figure 7.3: Voltage variation (p.u.) of the curtailment model on the modified IEEE-33 at T_2

The importance of the Curtailment model lies in the Fixed Reconfiguration model, where a generation curve with exceeded productions are presented. The optimization model is infeasible (no solution) with this generation curve that violates voltage constraints at T_1 and T_2 .

Table 7.2: Power Curtailment model on a modified IEEE-33

	T_1	T_2	T_3
Obj. function	0.2581	0.2581	0.2581
Power flow	0.221	0.221	0.0593
$curt(31)$ (MW)	5	5	0
$curt(32)$ (MW)	3.36	3.36	0
$V(31)$ (p.u)	1.1	1.1	1.066
$V(32)$ (p.u)	1.1	1.1	1.066

From Table 7.2, the Curtailment model is tested. T_1 , T_2 , and T_3 are the x-axis for the generation curve $\{5, 5, 0.4\}$ placed on buses 31 and 32. The power flow is the load flow simulation using Pandapower on the feasible configuration (one fixed topology for all curve points) at each point. For a vertex u , the variable $curt(u)$ represents the amount of curtailed active power at the vertex u in MW. $curt(u)$ is null for all buses except for buses 31 and 32, where exceeded production is identified. On buses 31 and 32, the voltage reaches its limit with the curtailed active power, which is expected as the Curtailment model curtails the power until the voltage limit (fixed at 1.1 p.u.) is reached. In Fig. 7.3, the voltage of all buses obtained by the Curtailment model at time T_2 is shown. Moreover, at the instant T_3 , we can see that no power reduction has taken place, since there is no voltage limit violation at any of the vertices 31 and 32.

On the other hand, the Relaxation Voltage model is tested on a modified IEEE-33 bus network applied to the Fixed Reconfiguration model (Section 6.2.1). Generation is placed on bus 31 with generation curves in two cases. Case 1 has a generation curve of $\{0.15, 0.6, 0.3\}$, which does not present any exceeded generations. Case 2 has a generation curve of $\{0.15, 5, 0.3\}$, where an exceeded generation is identified at $T = 2$.

Table 7.3: Case 1
on a modified IEEE-33 for the relaxation voltage model

	Obj. function	$\Delta(u, t), \forall u, t$
MIQP 6.2.1	0.1502	-
Relaxation voltage model	0.1501	0

From Table 7.3, the Fixed Reconfiguration model and the Relaxation Voltage model are compared. They present the same objective function. The small difference is due to the sensitivity of the variable $\Delta(u, t) \forall u \in G, t \in \{0.15, 0.6, 0.3\}$ in the Relaxation Voltage model. Moreover, $\Delta(u, t) = 0 \forall u \in G$ in the Relaxation Voltage model, which means that the two models have the same voltage on all network buses, and the relaxation variable Δ is null. On the other hand, in Case 2, where exceeded generation is identified, the MIQP model is infeasible. However, in the Relaxation Voltage model, which is feasible, $\Delta(31, 2) = 0.012$ at time $T = 2$. On all other buses, this variable is null. The same applies for other $T \neq T_2$, which is logical because the exceeded generation is present at bus 31 at time $T = 2$, where the voltage limits are violated.

7.5 Conclusion

In this chapter, based on the Fixed Reconfiguration model for a load-curve Distribution Network Reconfiguration (DNR) problem, two models are presented to address the impact of high levels of generation integration. This solves the problem where the solver might not be able to find a feasible configuration that satisfies the constraints at all time instants in the Fixed Reconfiguration model of load-based optimization constraints. The proposed constraints are tested on a modified IEEE-33 bus network under various generation scenarios. The obtained results align with the fact that the network should curtail its exceeded generation to a point where the voltage limit is respected. Further investigations could be conducted in cases where the cost of the curtailment is included in the objective function.

Chapter 8

Conclusions and Perspectives

This thesis tackles different aspects of the Distribution Network Reconfiguration (DNR) methodologies in the context of optimizing power losses for distribution networks. The DNR problem, known as NP-complete due to the search space that is not bounded, is solved using constraint programming by proposing a Mixed Integer Quadratic Programming (MIQP). The main problem was how to reduce the solver's computational time when the input of the DNR is large-scale distribution networks. The different methodologies in this context are applied in the case of a single operating point (*load, prod*) where the solver's computational time remains large. The first methodology was an algorithm applied to the graph in the input for the Mixed Integer Quadratic Programming (MIQP) used in order to reduce the solution's search space for the commercial solver used (Cplex, Gurobi). This method accomplishes the goal by reducing the solver's computational time using two types of network reduction: the first proposed by this thesis, and the second from the literature.

After this contribution, a method for eliminating low-impact switches in the distribution networks is presented. The goal is to find the most impactful switches in terms of DNR and use them as optimization variables, while setting the state of less impactful switches as their initial one and using it as data in the MIQP. This method has a phase of identifying these most impactful switches. The identification phase is done by running the DNR (formulated as an MIQP) sequentially on a set of initial operating points, and then, based on a coefficient defined for each switch, each one is classified as most impactful or low-impact in solving the DNR problem. After testing this method on a 2,588-bus realistic network, the results showed that the proposed method greatly improved computational time, making it roughly 177 times faster in the case of a single operating point. As a perspective for this contribution, future works should include a procedure to determine the most representative initial operating points that will be used to classify the different switches.

Next, we present a generalization of the Single Reconfiguration case, which was used in addressing the problem of reducing the solver's computational time. A study of load-curve-based optimization for the DNR problem is presented, and a comparison between the different possible cases is made. Then, the case of *Fixed Reconfiguration* is chosen as the best option in terms of load-curve optimization. It consists of finding a single feasible configuration that is optimal for a specific instant and respects the constraints of other

instants without being optimal for those.

At this point, and in the context of high integration of decentralized generation, the grid can lose its stability. Moreover, in line with our thesis, the solver might not be able to find a feasible configuration that satisfies all the time instants constraints in the presence of excess generation at specific instants. Power curtailment is a solution where the goal is to curtail the amount of excess power in a way that respects the maximum voltage limit. It is done by relaxing the power balance constraints to quantify the amount of curtailed power.

Therefore, this thesis presents a comprehensive study on the DNR problem to optimize power losses in different cases of load and generation, while solving different problems, starting with the solver's computational time in a single-point case and extending this case to load-curve-based optimization. The thesis also addresses various challenges, including high integration of decentralized generation, which is a significant future challenge for Distribution System Operators (DSOs).

Chapter 9

Résumé Etendu en Français

9.1 Introduction

Cette thèse porte sur l'étude du problème de reconfiguration du réseau de distribution (DNR). Le problème DNR trouve son application dans l'optimisation des performances des réseaux de distribution électrique, réduisant les pertes de puissance et améliorant l'efficacité du réseau. Les réseaux de distribution font partie des systèmes électriques, souvent sujets à des pertes de puissance qui génèrent des coûts lors de l'exploitation. Modifier la configuration du réseau pour fournir un meilleur flux d'énergie, minimiser les pertes et assurer un service fiable est une méthode clé pour résoudre ces problèmes : c'est le concept même du problème du DNR. Le problème DNR est NP-complet, ainsi, déterminer une configuration optimale nécessite des calculs exponentiels en fonction du nombre d'interrupteurs dans le réseau, qui peut être important dans les réseaux à grande échelle. Cela est dû au grand espace de recherche des configurations possibles et à la nécessité de satisfaire des contraintes opérationnelles telles que les limites de tension et l'équilibrage des charges. L'approche utilisée dans cette thèse pour résoudre le problème DNR est le Mixed Integer Quadratic Programming (MIQP). Une comparaison entre différentes méthodes pour résoudre le problème DNR est présentée, suivie d'une justification de l'utilisation de l'approche MIQP. Les contributions résident dans la réduction du temps de calcul du solveur de cette approche pour traiter la reconfiguration à point unique, en considérant un seul point de fonctionnement.

Sur un réseau de distribution, chaque point du réseau, qu'il consomme de l'énergie, ou en produise, le fait de façon variable au cours du temps. Dans l'idéal, on aimerait pouvoir calculer une configuration optimale et l'appliquer à chaque "instant" dans le réseau. Cependant, de nombreuses limitations interdisent cela, et notamment :

- la notion d'instant dans un réseau électrique et de la mesure est discrète, car la granularité de mesure des flux est de l'ordre de 10 minutes.
- les points de mesure instantanée dans le réseau électrique sont limités aux départs des postes sources, et aux consommateurs et producteurs importants, ne représentant, sur un réseau rural, qu'une partie minoritaire des flux.
- les actionneurs permettant de modifier la configuration des flux ont une durée de vie (en termes de changement d'états) limitée, ce qui rend une utilisation à faible granularité temporelle contre-productive d'un point de vue économique.

- les interrupteurs que l'on trouve sur un réseau rural sont soit manuels, requérant, pour être manipulés, le déplacement d'un technicien sur place, soit automatiques. Cependant, même dans ce second cas, une manipulation dure plusieurs secondes à dizaines de secondes (établissement de la liaison radio, puis action).

Par conséquent, une approche d'optimisation basée courbe de charge sera limitée dans ses actions, et dans sa granularité temporelle. Le Chapitre 6 traitera de ce point, considérant qu'il nous faudra trouver une unique configuration permettant de minimiser les pertes tout en respectant les contraintes étant donnée des courbes de charge et de production escomptées. L'optimisation basée sur la courbe de charge est donc une généralisation de la reconfiguration à point unique, en considérant les charges et les productions dynamiques au fil du temps. Une comparaison entre différents cas de reconfigurations multiples (dynamiques) dans ce contexte est présentée. Les défis posés par l'intégration de la production décentralisée, qui peut déstabiliser le réseau et compliquer le processus de reconfiguration, sont également abordés. Dans l'ensemble, les contributions de cette thèse améliorent l'efficacité de calcul du solveur tout en répondant aux défis posés par la forte intégration de la production distribuée, un problème opérationnel spécifique dans les réseaux à grande échelle.

Parfois, un point particulier de fonctionnement dans la courbe de charge considérée peut être la source de contraintes fortes sur le réseau. Par exemple, une production d'ENR très importante en un point du réseau durant une courte période, pourra exclure des configurations réduisant fortement les pertes, car durant une courte période, cette production génère des hausses de tension ne permettant pas de respecter les contraintes. Dans les réseaux de transport, il est possible pour le gestionnaire de réseau de demander à un producteur d'écarter sa production durant une certaine période. La possibilité d'utiliser ce levier peut alors permettre une configuration réseau qui, sur la durée de la fenêtre temporelle considérée, écartera temporairement une production afin que la configuration respecte les contraintes, autorisant une configuration réseau réduisant les pertes.

La thèse est donc structurée pour analyser plusieurs techniques basées MIQP, en commençant par le problème DNR de base dans la reconfiguration à point unique, et en progressant vers des problèmes plus complexes comme les reconfigurations multiples et en relevant le défi de la forte intégration des générations décentralisées, avec des solutions telles que la réduction de puissance et la relaxation de tension.

9.2 Contexte et thématique : Labcom ALIENOR

La modernisation du système électrique passe par une forte intégration des énergies renouvelables dans les réseaux de distribution. En effet, il est devenu indispensable de gérer dynamiquement les flux d'énergie. Les technologies de smart grids sont déployées dans les réseaux électriques français et européens ainsi que la valorisation des données. Les gestionnaires de réseau de distribution (GRD) pourront agir sur le système électrique avec l'intégration des Technologies de l'Information et de la Communication de Nouvelle Génération (NTIC). Cela conduit à une distribution d'électricité efficace, économiquement viable et sûre.

C'est dans ce contexte que la société SRD et le laboratoire LIAS ont décidé d'associer leurs expertises pour créer conjointement le Laboratoire Commun ANR @LIENOR (LabCom) (Laboratoire pour l'Intégration des Nouvelles Energies et l'Optimisation des Réseaux). Ce laboratoire commun constitue la continuité d'un partenariat qui avait déjà abouti au développement d'un prototype d'outil IMAGE (Intelligent Management and Energy Management system) qui optimise les schémas d'exploitation sur une période ou un horizon temporel. Le LabCom @LIENOR est essentiel non seulement à l'intégration continue des ENR, mais permet également d'industrialiser l'outil IMAGE pour le rendre applicable et fonctionnel dans tout environnement industriel en ajoutant une approche stochastique et dynamique qui prend en compte le caractère variable et intermittent de la consommation et de la production d'ENR.

9.3 Réseaux de Distribution et Gestionnaires de Réseau de Distribution

9.3.1 Les réseaux de distribution

Les réseaux de distribution en France sont des systèmes adaptatifs, avec le rôle de fournir de l'électricité de manière localisée aux utilisateurs finaux dans différentes régions. Géré par des GRD tels qu'Enedis et SRD, le réseau de distribution en France suit une structure hiérarchique englobant divers composants, notamment les lignes de distribution, les transformateurs, les sous-stations et les technologies de réseau intelligent. En fait, le réseau de distribution SRD intègre des technologies de réseau intelligent qui permettent une communication en temps réel, facilitant la précision, la détection des défauts et l'adaptation aux variations de charge dynamiques. Le réseau de distribution français continue de s'étendre pour s'adapter à l'intégration croissante des sources d'énergie renouvelables, à la gestion de la demande et à l'infrastructure de comptage avancée. Le niveau de tension des réseaux de distribution en France est appelé moyenne tension (HTA), allant de 20 kV à 50 kV, et il est responsable de la distribution de l'énergie des sous-stations de transmission aux sous-stations de distribution. Dans cette thèse, on définit en détails chaque composant du réseau de distribution.

9.3.2 Les composants du réseau de distribution

Le réseau de distribution est constitué de plusieurs éléments essentiels, parmi lesquels : les interrupteurs (switch), les transformateurs, les lignes, les productions décentralisées, etc. Les pertes par effet Joule, dues à la résistance dans les lignes électriques, sont responsables de pertes d'exploitation. Les réduire permettrait donc de réduire les coûts d'exploitation. Cependant, la tension de l'onde délivrée aux clients doit être dans un intervalle de tolérance par rapport à la tension cible, typiquement sur un réseau basse tension, en France, de $\pm 10\%$ par rapport aux 230V attendus. Ces 10%, sur un réseau rural, pourront être arbitrairement décomposés en $\pm 5\%$ de tolérance sur le réseau moyenne tension, qui est celui qui est configurable, entre postes sources et poste de transformation basse tension (BT), et $\pm 5\%$ de tolérance sur le réseau BT, usuellement statique dans les installations rurales.

Alors que les réseaux de distribution continuent d'intégrer les énergies renouvelables décentralisées (principalement de sources photovoltaïques et éoliennes), pouvant générer des augmentations de tension localement, la gestion et la minimisation des pertes électriques sous contraintes de tension devient fondamentale pour les gestionnaires des réseaux de distribution.

9.3.3 Load Flow

L'analyse des flux de charge (Load Flow), également connue sous le nom d'analyse des flux de puissance, est un aspect fondamental de l'analyse des systèmes électriques. Elle garantit que les amplitudes de tension et les angles de phase à tous les sommets (bus) du système restent dans des limites acceptables pour maintenir la stabilité et la fiabilité du système tout en garantissant l'équilibre entre les générations et les charges afin d'éviter la surcharge des composants du système. L'ensemble de l'analyse du flux de charge

utilisée pour analyser et comprendre le comportement en régime permanent des réseaux électriques dépend de la topologie du réseau (maillée, radiale...).

Les méthodes utilisées pour identifier les différents paramètres d'un ouvrage électrique sans topologie spécifiée (par exemple une topologie arborescente) sont les méthodes matricielles. L'une des méthodes les plus connues est la méthode de Newton-Raphson qui est une méthode itérative.

9.3.4 Optimisation

En complément aux méthodes itératives, qui considèrent une unique configuration du réseau, la tâche de sélectionner la meilleure topologie, c'est-à-dire la résolution de DNR, utilise des techniques d'optimisation, formulé avec des objectifs et des contraintes, afin d'identifier la reconfiguration optimale du réseau. Cependant, puisque la vérification de l'état électrique pour un point de fonctionnement nécessite une étude itérative, l'analyse des flux de charge est amené à être approximé par une linéarisation. Ce qui complexifie le processus est qu'il n'y a pas de manière conservatrice de procéder : en effet, si l'on devait uniquement se prévenir des chutes de tension (resp., des sur-tensions), nous pourrions utiliser un modèle linéaire conservatif sous-estimant (resp., sur-estimant) le modèle itératif. Dans le cas du DNR sous contrainte de tension, les deux cas sont à considérer. Cela explique pourquoi une topologie optimale n'est pas garantie d'être optimale au sens de l'analyse de load flow.

En général, la principale différence entre les méthodes d'analyse du flux de charge réside dans leurs résultats et leurs applications. L'analyse du flux de charge fournit l'état d'un réseau donné, y compris les valeurs de tension à chaque bus, la puissance circulant dans les branches, les niveaux de tension à chaque sommet du réseau, etc. En fait, il n'est pas possible de résoudre une linéarisation de l'équation non linéaire du flux de charge d'une manière strictement exacte. Cependant, lorsque nous parlons d'optimisation, nous faisons référence à la modification de la topologie ou de l'état du réseau. Il n'est pas possible d'y parvenir en appliquant l'analyse du flux de charge. En revanche, la nouvelle topologie obtenue grâce à l'optimisation peut être utilisée dans l'analyse du flux de puissance pour vérifier divers paramètres dans cette nouvelle topologie, tels que les limites de tension. En outre, l'optimisation permet aux GRD de prendre des mesures et d'apporter des ajustements au réseau donné. L'une de ces actions consiste à modifier la topologie du réseau.

9.3.5 Problème de Reconfiguration des réseaux électriques (DNR)

Le problème de la reconfiguration du réseau de distribution (problème DNR) est la manière de reconfigurer (changer) l'état (de ON à OFF ou de OFF à ON) des interrupteurs dans le réseau de distribution. Cette reconfiguration diffère de la première configuration (c'est-à-dire l'état initial des interrupteurs) par la quantité de pertes de puissance qui est inférieure aux pertes de puissance de la première configuration.

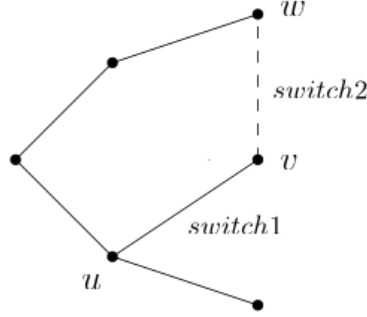


Figure 9.1: Le graphe sous-jacent

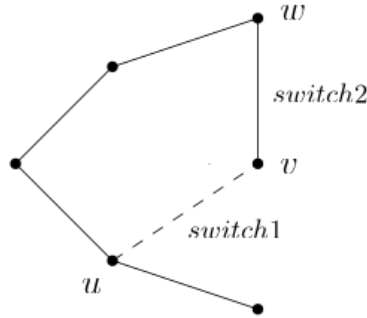


Figure 9.2: Une configuration réalisable

Le réseau de distribution est représenté par un graphe sous-jacent $G = (V, E)$ qui est construit sur la base des données GPS de chaque ligne électrique, interrupteur, charge, génération, transformateur, etc. G représente chaque composant électrique comme un sommet ou une arête. Chaque branche électrique est représentée par une arête entre deux points avec un dictionnaire de ses caractéristiques (résistance, réactance, etc.). Chaque interrupteur est également représenté comme une arête s'il est activé. En fait, un interrupteur peut connecter deux sommets (état ON, i.e., fermé) ou déconnecter deux sommets (état OFF, i.e., ouvert). Les sommets du graphe sont l'ensemble des charges, des générations distribuées (photovoltaïque, éolien, etc.), des sources (transformateurs HTB/HTA). Soit $G = (V, E)$ le graphe sous-jacent où V est l'ensemble des sommets (bus) et E l'ensemble des arêtes (Fig. 9.1).

Une configuration réalisable (solution) est une configuration possible de l'état des commutateurs qui respecte les différentes contraintes exigées par le GRD. Elle représente un graphe dirigé radial connecté (Fig. 9.2). Dans ce contexte, un graphe radial est une forêt : chaque composante connexe doit contenir un et un seul poste source, qui constitue la racine d'un arbre, chaque nœud du réseau (charge, i.e. consommateur, ou production décentralisée) étant relié par un unique chemin à un et un seul poste source. Notons que si une composante connexe ne contenait pas de poste source, on parlerait d'îlotage, ce qui sort du périmètre de cette thèse. La contrainte de poste source unique est typiquement une contrainte provenant du gestionnaire de réseau HTB, qui proscriit la possibilité de lier deux postes sources différents dans le réseau HTA.

La résolution du problème DNR relève du domaine de la recherche opérationnelle.

Une solution naïve alternative au problème du DNR consisterait à énumérer toutes les configurations possibles et à calculer le montant des pertes générées par chaque configuration. Cependant, étant donné le nombre très élevé de possibilités (16698 commutateurs, conduisant à plus de 16698 variables binaires, pour le réseau SRD), il est impossible de procéder à une recherche exhaustive de toutes les solutions ou effectuer une recherche exhaustive de toutes les solutions. Toutefois, on peut envisager d'en répertorier un certain nombre en fonction de certains critères liés à la connaissance du réseau étudié, ou d'utiliser des heuristiques ou méta-heuristiques pour parcourir cet espace gigantesque de solutions possibles.

Le problème de la reconfiguration du réseau est donc NP-hard au sens fort [Kho+18], et les différentes techniques utilisées pour sa résolution sont partagées entre les heuristiques, les méta-heuristiques et les méthodes dites d'optimisation exacte.

9.3.6 Synthèse

En conclusion, l'analyse des flux de charge nécessite la connaissance de la topologie du réseau, tandis que la reconfiguration du réseau par les GRD nécessite des méthodes d'optimisation pour identifier la meilleure solution parmi les différentes configurations de commutation. La formulation du problème de reconfiguration du réseau de distribution (DNR) permet d'obtenir une solution optimale si la fonction objective et les contraintes sont convexes. Cette thèse s'appuie sur un modèle convexe pour le problème DNR, et ses contributions basées sur ce modèle.

9.4 Approches de résolution du problème DNR : Méthodes Exactes

Les méthodes exactes, ou méthodes déterministes, sont des algorithmes qui cherchent à trouver la solution globale optimale à un problème d'optimisation en un temps fini, et prouver son optimalité. En fait, malgré le fait que le problème DNR soit NP-difficile, les méthodes exactes peuvent toujours être utilisées pour résoudre efficacement le problème DNR en utilisant des solveurs commerciaux (Cplex, Gurobi, etc.). En effet, avec les progrès des puissances de calcul et d'implantation des solveurs, le fait d'avoir un problème NP-complet aujourd'hui ne signifie pas qu'il est impossible de le résoudre de façon optimale, contrairement par exemple à un problème $\text{NP}^{\text{Co-NP}}$ [Bar21].

La principale raison en est que la taille du problème peut être gérée par le solveur de manière à ce qu'il puisse décomposer le problème en sous-problèmes et trouver une solution optimale ou quasi-optimale. En outre, les progrès réalisés dans le domaine du matériel informatique et des logiciels ont augmenté la puissance de calcul disponible pour résoudre les problèmes d'optimisation. Par exemple, dans la méthode exacte branch and bound, la taille de la recherche arborescente est exponentielle avec la taille du problème. Ainsi, grâce aux capacités intenses des logiciels d'exploration de l'espace de recherche et à certaines heuristiques de recherche, le calcul de la solution optimale devient possible.

C'est pourquoi les méthodes d'optimisation exactes sont utilisées pour résoudre le problème du DNR dans cette thèse. Un Mixed Integer Quadratic Programming (MIQP) est utilisé dans cette thèse et est présenté.

9.4.1 Généralités

Un réseau de distribution fonctionne généralement avec une topologie en forêt (un arbre pour chaque source, car deux sources ne peuvent pas être connectées) en raison de la simplicité de conception des dispositifs de protection pour cette configuration. Cependant, les boucles sont possibles, bien qu'elles soient généralement laissées ouvertes (c'est-à-dire que le fonctionnement de la boucle reste ouvert). Cette approche se justifie principalement par la nécessité de rétablir l'alimentation dans les zones touchées par des coupures, telles que celles causées par des courts-circuits sur une ligne, ou l'endommagement d'une ligne ou d'un dispositif électrique.

Dans des conditions normales d'exploitation, l'interrupteur ouvert de la boucle n'est soumis à aucune contrainte particulière tant que les lignes ne sont pas surchargées et que les tensions nodales restent dans les limites spécifiées. Souvent, cet interrupteur ouvert est sélectionné en fonction de certains critères d'optimisation, tels que la minimisation des pertes de puissance. Dans certains réseaux de distribution où le nombre de boucles est faible et où les boucles sont indépendantes les unes des autres (c'est-à-dire non adjacentes), le nombre de combinaisons possibles pour l'ouverture des branches est limité. En évaluant tous les cas possibles, il est relativement simple d'identifier les points d'ouverture optimaux.

Cependant, lorsque les boucles ne sont plus indépendantes, le nombre de possibilités

augmente de façon exponentielle.

9.4.2 Modèle MIQP

Le réseau de distribution est représenté par un graphe non orienté $G = (N, E)$ où N est l'ensemble des sommets et E l'ensemble des arêtes. Chaque branche (ligne électrique, interrupteur) est représentée par une seule arête. Chaque sommet représente une charge, un producteur ou un sommet sans charge ni producteur.

G est l'entrée du modèle MIQP qui est détaillé dans la thèse.

- **Fonction objective:** *Minimiser* pertes de puissance (effet Joule)
- **Contraintes:**
 - *Radialité* de la topologie
 - *Flux Fictifs* : Contraintes pour éviter les boucles qui peuvent être créées par des générations alimentant les consommateurs indépendamment du transformateur. C'est ce qu'on appelle l'îlotage
 - *Loi des nœuds* : La conservation de la puissance active et réactive dans le réseau
 - *Limitation de la tension* : Le contrôle de la tension sur chaque sommet du graphe
 - *Limite des puissances pour les branches*: Restriction de la puissance apparente dans chaque branche
 - *Limites de puissance au niveau des sources*: Limitation de la puissance apparente des sources

9.4.3 Défis et contributions

Les méthodes d'optimisation *exactes* ont l'avantage d'être générales et de prouver l'optimalité ou la distance à l'optimum de la solution proposée. Cependant, bien qu'elles soient très performantes pour les problèmes linéaires, voire quadratiques, des avancées sont encore nécessaires pour la résolution de problèmes non linéaires. En outre, la convexité du problème est une condition nécessaire à l'utilisation de certains solveurs, la difficulté pour l'utilisation de ces techniques est donc de modéliser le problème de manière linéaire ou quadratique et convexe. L'inconvénient réside dans l'espace de recherche des solutions, c'est-à-dire toutes les combinaisons possibles de variables à la fois binaires et continues qui définissent toutes les solutions potentielles. Le fait est qu'avec l'augmentation du nombre de variables décisionnelles et continues (qui dépend de la taille du réseau), la taille de

l'espace de recherche augmente. Par conséquent, le temps de calcul du solveur pour toute formulation MIQP appliquée à ce réseau augmentera.

Voici l'objectif principal de cette thèse : réduire le temps de calcul du solveur pour la formulation MIQP appliquée au réseau de distribution SRD. Les contributions de cette thèse utilisent les réseaux académiques et le réseau SRD comme tests dans le but de réduire le temps de calcul du solveur pour la formulation MIQP, et le rendre utilisable à l'échelle d'un GRD rural.

L'objectif est de réduire le temps de calcul du solveur pour la formulation MIQP. En effet, le temps de calcul du solveur dépend de la taille du graphe représentant le réseau, typiquement de la taille du réseau.

Ces considérations nous ont amenés à utiliser divers moyens de modélisation, assemblés à partir de l'état de l'art, pour proposer deux modélisations, présentées sous formes de contraintes dans le chapitre 3 en anglais, respectivement à la section 3.5 et la section 3.6.

Dans la section suivante, nous présenterons les différentes approches pour résoudre le problème du DNR. Ces approches consistent en des heuristiques, des méta-heuristiques et des méthodes exactes. Ensuite, les contributions seront annoncées dans les chapitres suivants.

Dans notre tentative avec le réseau SRD, les méthodes exactes sont utilisées. Une formulation MIQP pour le problème DNR est proposée. Le modèle présenté est enrichi de contraintes supplémentaires, prenant en compte les contraintes de puissance réactive et de flux fictif, qui répondent à la forte intégration des énergies renouvelables et empêchent la création d'îlots dans la solution.

En raison de la taille importante du réseau de distribution SRD, qui comprend 45147 bus avec 16698 interrupteurs, il y aura un total de 16698 variables binaires, ce qui, même sur des calculateurs actuels, requière des dizaines d'heures de calcul pour un seul point de fonctionnement du réseau. Nous pouvons donc prévoir que le temps de calcul du solveur sera trop long si nous appliquons la formulation MIQP au réseau SRD, d'autant que nous visons par la suite une optimisation étant donnés plusieurs points de fonctionnement définissant des courbes de charges.

9.5 Une Méthode de Réduction de réseaux pour le Problème de Reconfiguration des Réseaux (DNR)

Dans le chapitre précédent, nous avons défini les objectifs de la thèse et la feuille de route des contributions. Le travail se concentre sur la réduction du temps de calcul du solveur. En particulier, le travail est basé sur le problème de la reconfiguration du réseau de distribution (DNR) qui peut être modélisée à l'aide d'un problème de Mixed Integer Quadratic Programming (MIQP). Pour SRD, l'objectif est à la fois de réduire le temps de calcul du solveur pour le modèle MIQP qui a été développé dans [Ali17], tout en prenant en compte des contraintes supplémentaires comme la puissance réactive et le contrôle de la variation de tension.

La première façon de réduire le temps de calcul du solveur pour le modèle MIQP proposé dans la thèse consiste simplement à réduire la taille du graphe sous-jacent en entrée du modèle MIQP, tout en préservant l'équivalence au niveau électrique entre graphe réduit et graphe original. Le chapitre présente en détails la méthode de réduction du réseau. Cette méthode est testée sur une agence du réseau SRD.

9.5.1 Introduction

La principale contribution de ce chapitre est de fournir une méthodologie de réduction des graphes de réseau. Cette réduction, basée sur les méthodes de la théorie des graphes, tend à réduire la taille du graphe sous-jacent (représentant le réseau de distribution). Elle consiste en la suppression séquentielle des sommets jusqu'à l'obtention d'un cycle, ou d'une source dans le graphe sous-jacent. Après la présentation de la réduction du réseau, une autre réduction tirée de [Ali17] est effectuée. Les expériences et les comparaisons avant et après l'application de ces réductions seront réalisées dans la section suivante.

9.5.2 Réduction de graphes

La réduction du réseau commence, séquentiellement, pour chaque feuille et l'élimine si le cardinal de ses voisins est un et un seul. Si c'est le cas, le voisin est sélectionné et ce processus est itératif jusqu'à atteindre un sommet sélectionné avec 2 voisins ou plus ou un sommet sélectionné qui est une source. Ce sommet sélectionné, où le processus se termine, est appelé sommet terminal. Dans la figure 9.3, les sommets terminaux sont w_0 et *source*.

Après avoir effectué ce processus sur toutes les feuilles, il reste à vérifier si les limites de variation de tension sont respectées dans les sous-ensembles supprimés pour chaque sommet terminal. Ceci est fait en exécutant un programme linéaire qui est présenté dans la section suivante. En effet, sans vérification des limites de variation de tension sur les ensembles retirés, la méthode ne sera pas équivalente au réseau originel.

Comme nous pouvons l'observer, dans la réduction du réseau, l'ensemble des sommets supprimés est constitué des chemins menant aux feuilles. En fait, ces chemins dans le graphe sous-jacent ne sont pas utiles pour le modèle MIQP. Pour le prouver, supposons qu'un commutateur soit contenu dans l'un de ces chemins. Tous les interrupteurs sont

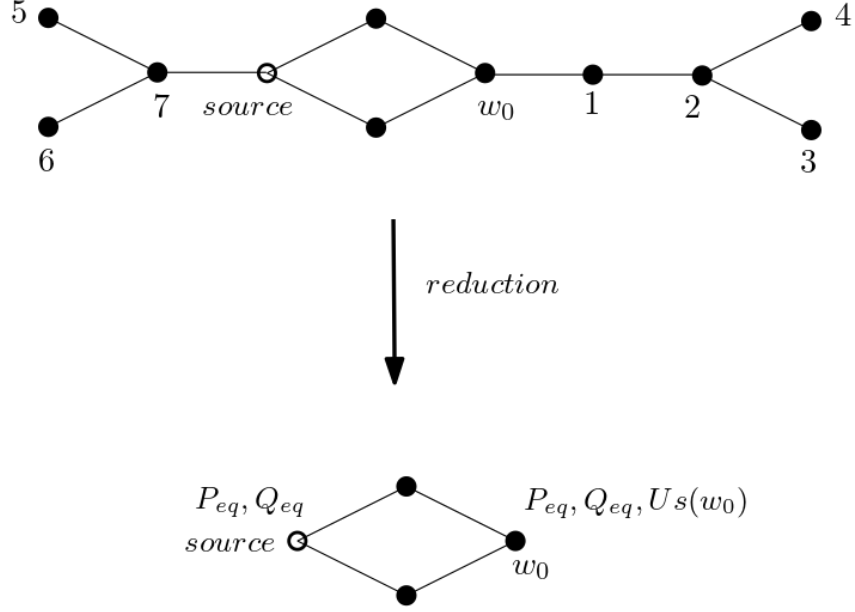


Figure 9.3: $\{1,2,3,4\}$ est fusionné en w_0 et $\{5,6,7\}$ en la source

fermés dans le graphe sous-jacent. Après avoir appliqué le MIQP au graphe sous-jacent en entrée, si cet interrupteur change d'état, l'extrémité de ce chemin sera déconnectée. Par conséquent, les interrupteurs contenus dans ces chemins resteront fermés dans la solution réalisable donnée par le MIQP et la suppression de l'ensemble du chemin réduira les variables binaires représentant ces interrupteurs ainsi que les variables continues pour chaque arête de ce chemin.

Ainsi, en supprimant ces chemins, la solution réalisable du MIQP qui prend le graphe équivalent en entrée ne sera pas affectée.

L'objectif est d'obtenir un réseau (graphe) équivalent au réseau initial. Après avoir appliqué la réduction du réseau, et la suppression des ensembles $s(l_0)$ associés à chaque feuille l_0 , nous devons déterminer les puissances actives et réactives équivalentes au sommet terminal de l'ensemble $S(l_0)$ et les valeurs minimales et maximales de la tension à ce sommet.

Les valeurs des puissances actives et réactives sont calculées par l'application des contraintes de la loi des nœuds, elles consistent en un système de n équations à n inconnus au niveau du nœud aggloméré (w_0 ou *source*). Si le nœud terminal (w_0 dans la Fig. 9.3) n'est pas une source, il faut vérifier que la tension au niveau de chaque nœud supprimés associés à ce nœud respecte les bornes. Pour cela, en plus d'utiliser la modélisation sur le réseau réduit et ses nœuds agglomérés, nous calculons les limites de tension à w_0 pour les utiliser dans le MIQP appliqué au réseau réduit. Pour ce faire, une nouvelle limite de tension est définie pour chaque sommet aggloméré. Cette limite est considérée dans l'optimisation globale et est appliquée pour résoudre le problème DNR pour le graphe réduit. Deux programmes linéaires appliqués aux parties fusionnées (appelé G_0 pour une feuille l_0).

$\forall u \in G_0 \text{ t.q. } N^{in}(u) \geq 1, \forall v \in N^{in}(u) :$

$$Us(u) = Us(v) - 2(R(u, v)yp(v, u) + X(u, v) yq(v, u)) \quad (9.1)$$

Le premier programme linéaire trouvera la limite inférieure de la tension à w_0 en utilisant la contrainte précédente (4.1) dans le cadre de la fonction objectif suivante :

$$\min Z_{presolve} = Us(w_0) \quad (9.2)$$

Le second programme linéaire sera, à l'instar de la borne inférieure, la borne supérieure de la tension à w_0 qui est obtenue avec (9.1) et

$$\max Z_{presolve} = Us(w_0) \quad (9.3)$$

Après avoir obtenu le graphe réduit, une autre réduction adaptée de [Ali17] est appliquée. Elle consiste à fusionner les branches non contrôlables en série, qui ne comprennent aucun sommet de charge ou de génération, en une seule arête. La nouvelle arête a une résistance/réactance équivalente, qui est la somme des résistances/réactances des branches fusionnées, et une capacité maximale de flux de puissance apparente qui est égale à la capacité minimale de flux de puissance apparente parmi les branches fusionnées.

9.5.3 Synthèse

La réduction du réseau et l'adaptation de la réduction de [Ali17] sont testées sur une agence du réseau de distribution SRD. Sur cette agence [Kar], le solveur utilisé est Gurobi Optimizer version 10.0.1 avec deux paramètres modifiés : MIPGap (écart d'optimalité relatif) et Heuristics fixé à 0. L'objectif est de s'assurer que le solveur se termine lorsqu'une solution optimale est trouvée (MIPGap) et sans heuristique supplémentaire qui tendrait à réduire l'espace de recherche. Ce calcul est effectué sur un ordinateur équipé d'un processeur Intel(R) Core(TM) i5-9500 CPU @ 3.00GHz avec 32 GB de RAM. Le MIQP utilisé est celui avec variables binaires bidirectionnelles présenté dans la thèse. Nous comparons le temps de calcul du solveur pour cette MIQP sur l'agence avant et après réduction, afin d'interpréter l'efficacité des méthodes de réduction du réseau en termes de temps de calcul du solveur.

Le meilleur résultat (sans tenir compte du temps de pré-résolution) est obtenu en effectuant les deux réductions de manière séquentielle, ce qui se traduit par un meilleur temps de calcul pour résoudre la formulation du problème DNR et une efficacité accrue dans le traitement des réseaux à grande échelle. Cette méthode a un potentiel d'utilisation si elle produit des résultats supérieurs à ceux de l'absence de réduction de graphe en termes de temps de calcul du solveur. Des recherches supplémentaires sont nécessaires pour comprendre pourquoi elle augmente le temps de calcul dans certains cas. En outre, cette méthode de réduction peut être testée sur un problème DNR avec contraintes supplémentaires.

Dans le chapitre suivant, une méthode d'élimination des commutateurs à faible impact est présentée : elle a pour objectif de réduire le temps de calcul du solveur en détectant les commutateurs les plus impactants. Elle se base sur le fait que les conducteurs de

réseau de distribution sont capables de choisir manuellement des configurations du réseau, notamment parce qu'il a été dimensionné pour assurer des flux via des lignes de bonne qualité de certains postes sources pressentis comme étant ceux devant l'alimenter à telle ou telle charge. On peut faire une analogie avec un réseau routier, où des axes plus onéreux à construire, mais plus rapides, les autoroutes, ont été construits pour assurer des flux rapides de véhicules sur certains grands axes. Pour trouver un plus court chemin, il est alors plus utile de tester les solutions passant par ces grands axes, et de ne s'en éloigner légèrement en cas d'indisponibilité d'un tronçon, plutôt que d'analyser toutes les solutions alternatives passant par des chemins de traverse plus lents.

9.6 Méthode d'élimination des interrupteurs à faible impact pour le problème de reconfiguration des réseaux de distribution à grande échelle

La reconfiguration du réseau de distribution (DNR) consiste à modifier la topologie d'un réseau de distribution (DN) en changeant l'état de ses commutateurs, modifiant ainsi le chemin de circulation de l'énergie.

Dans le chapitre précédent, nous avons présenté une méthode de réduction de réseau qui réduit la taille du graphe représentant le réseau, réduisant ainsi le nombre de variables et de contraintes, et par conséquent, leur impact sur l'espace de recherche de la solution. Le but ultime est de réduire le temps de calcul du solveur pour la formulation en programmation quadratique mixte en nombres entiers (MIQP) du problème DNR.

Dans ce chapitre, nous présentons une contribution visant à diminuer le temps de calcul du solveur. Il s'agit d'une méthode permettant d'identifier les commutateurs les plus impactants pour le problème DNR. Les commutateurs les plus impactants restent sous forme de variables binaires, tandis que les variables binaires des commutateurs les moins impactants sont converties en données d'entrée (ON ou OFF fixé) pour maintenir leur état. Cette approche réduit efficacement le nombre de variables binaires, diminuant ainsi le temps de calcul. Les performances de la méthode sont évaluées à l'aide d'une simulation sur un réseau de distribution SRD réaliste de 2 588 bus. Les résultats montrent que la méthode proposée peut réduire le temps de calcul du DNR d'un facteur allant jusqu'à 177.

9.6.1 Méthode d'élimination des interrupteurs avec un faible impact sur le DNR

L'intuition est que tous les interrupteurs du réseau de distribution (DN) ne sont pas utiles pour la reconfiguration du réseau de distribution (DNR). Un ensemble de points de fonctionnement initiaux (OP) est choisi, où chaque OP a des valeurs spécifiques comme des coefficients de foisonnement pour les charges et les générations distribuées (DG) à chaque point du réseau. Le concept de cette méthode est d'exécuter la DNR séquentiellement à chaque OP initial, puis, pour chaque OP, une valeur continue $\in [0, 1]$ est déterminée pour chaque commutateur du réseau. Enfin, chaque commutateur est classé comme commutateur le plus impactant ou non. Les commutateurs les plus impactants resteront sous forme de variables binaires dans le MIQP avec une variable binaire par bord, et les commutateurs restants seront fixés dans leur état (1 ou 0). L'un des défis consiste à sélectionner un ensemble d'OP représentatifs de tous les scénarios possibles de charge et de production (par exemple, charge élevée, faible production).

Après avoir obtenu les résultats du DNR : $SW_ON(u, v)$ est calculé, ce qui représente, pour chaque interrupteur (u, v) , la valeur moyenne d'être ON (en pourcentage) pour les DNR effectués avec les OP initiaux :

$\forall(u, v) \in A_{SW} :$

$$SW_ON(u, v) = 100 \cdot \frac{\sum_{j=1}^{NIOP} D(u, v, j)}{NIOP} \quad (\%) \quad (9.4)$$

Où NIOP est le nombre de points de fonctionnement initiaux, et $D(u, v, j)$ représente l'état de l'interrupteur (u, v) (qui est $d(u, v)$) qui est obtenu par le DNR appliqué sur le $j - ime$ OP initial.

- Si un interrupteur (u, v) a une valeur de **$SW_ON(u, v) = 100\%$** , alors on considère qu'il a un faible impact sur le DNR (parce qu'il a été allumé tout le temps et n'a jamais changé), et il est assigné comme un arc non contrôlable avec : **$d(u, v) = 1$** .

- Si un interrupteur (u, v) a une valeur de **$SW_ON(u, v) = 0\%$** , il est également considéré comme n'ayant pas d'impact sur le DNR (parce qu'il est resté éteint tout le temps et n'a jamais été modifié), et il est défini comme un arc ouvert dans le DNR : **$d(u, v) = 0$** .

- Si un interrupteur (u, v) a changé entre différentes solutions trouvées pour les OP, c'est-à-dire **$SW_ON(u, v) \in]0\%, 100\%[$** , il est alors considéré comme impactant pour le DNR. Dans ce cas, **$d(u, v)$ est conservé comme variable d'optimisation¹**, et le commutateur (u, v) est inclus dans l'ensemble **SW_OV** (pour interrupteur variable d'optimisation), qui représente l'ensemble contenant tous les commutateurs qui sont considérés comme ayant un impact.

9.6.2 Expériences et résultats

Le solveur utilisé est Gurobi Optimizer version 10.0.1, sur un PC avec 11th Gen Intel(R) Core(TM) i5-1135G7 @ 2.40GHz 2.42 GHz 8,00 Go de RAM. La bibliothèque Pandapower [Thu+18] de Python est utilisée pour effectuer des flux de puissance (PF) sur les DN.

La méthode proposée est testée sur une agence réaliste du réseau de distribution SRD composée de DN à 2588 bus qui peut être obtenue à partir de [Kar] et testée dans la méthode de réduction du réseau dans le chapitre précédent, avec 403 commutateurs. Après avoir appliqué la méthode de réduction du réseau décrite au chapitre précédent, il reste 132 commutateurs. Les autres, qui sont supprimés après la réduction, sont considérés comme étant ON ².

La tension à la source est fixée à $1,03p.u.$. Pour toutes les différentes optimisations, le rapport entre la puissance réactive et la puissance active pour toutes les charges est de 0,1, et celui pour tous les GED est de 0 ³.

Les simulations peuvent être divisées en trois phases :

¹Par conséquent, sa valeur doit être déterminée par l'optimisation.

²Les autres interrupteurs sont nécessairement ON, car s'ils sont OFF, certains bus ne seront pas connectés à une source

³Ce qui signifie que lorsqu'on choisit une OP et qu'on modifie la puissance active, la puissance réactive est également modifiée.

Table 9.1: État des interrupteurs après élimination des interrupteurs peu impactants

	Modélisation des interrupteurs	Pourcentage (%)
interrupteurs restant variables	33	8.19
interrupteurs fixés	370	91.81
dont fermés	370	91.81
dont ouverts	0	0.0

Table 9.2: Resultats pour OP1 and OP2

	Pertes (kW)	Réduction des pertes (%)	Temps de calcul (s)
DNR classique OP1	6.34	-38.17	730.92
DNR simplifié OP1	6.34	-38.17	8.17
DNR classique OP2	41.66	-27.90	506.69
DNR simplifié OP2	41.66	-27.90	2.86

1- **Une première phase** où l'on identifie les commutateurs les plus importants.

2- **Une deuxième phase** au cours de laquelle l'optimisation du réseau avec seulement les commutateurs les plus importants est effectuée.

3- **Une troisième phase** où les résultats obtenus par le DNR avec les commutateurs les plus impactants sont comparés à un DNR classique où l'ensemble des commutateurs sont des variables binaires.

Phase1: Pour cette phase, six OP différents sont choisis dans le plan (k_{load}, k_{DG}) , de manière à représenter différents scénarios possibles que nous espérons représentatifs des charges. Nous choisissons ces OP relativement éloignés les uns des autres dans le plan (k_{load}, k_{DG}) , de manière à capturer le « comportement global » des commutateurs dans le réseau, et pas seulement sur une zone spécifique du plan. Ils ont été choisis pour être représentatifs des scénarios de forte charge et de faible génération (0,18,0,2), de faible charge et de forte génération (0,06,0,8), ainsi que de forte charge et de forte génération (0,2,0,8). Le choix des charges de manière représentative peut nécessiter l'intervention d'experts. On pourrait également utiliser des ensembles de données historiques basées sur la consommation, mais cela n'entre pas dans le cadre de cette thèse. Ensuite, le DNR est exécuté sur ces PO **séquentiellement**. Il en résulte le tableau 9.1, montrant le pourcentage moyen d'activation pour chaque interrupteur.

Les données sont présentées dans le tableau 9.1. Comme on peut le voir, pour les 6 PO initiaux, parmi les 403 commutateurs du DN, seuls 33 sont variables (8.19%), et 370 (91.81%) sont fixes, ce qui signifie que, au moins pour ces PO et cette DN, la grande majorité des commutateurs ne contribuent pas au DNR, en ce sens qu'ils peuvent être considérés comme des valeurs fixes plutôt que comme des variables d'optimisation. Nous remarquons également que les interrupteurs fixes sont tous ON (370), et qu'aucun d'entre eux n'est désactivé dans les solutions optimales pour les OP choisis. L'ensemble des interrupteurs variables SW_OV est également obtenu.

Comme le montre le tableau 9.2, qui affiche les résultats de quatre optimisations différentes, le DNR classique et le DNR simplifié (après application de la méthode d'élimination

des interrupteurs) ont tous deux convergé vers la même solution pour OP1 et OP2, malgré le fait que le DNR simplifié ne contrôle que 33 interrupteurs au lieu de 403 interrupteurs⁴. Cependant, en termes de temps de calcul du solveur, il est évident que la DNR simplifiée est beaucoup plus rapide que la DNR classique : **89,46 fois plus rapide** pour OP1 et **177,16 fois plus rapide** pour OP2, ce qui montre clairement l'avantage de la méthode proposée.

9.6.3 Synthèse

Dans ce chapitre, une méthode d'élimination des interrupteurs à faible impact a été proposée pour trouver les interrupteurs les plus impactants en termes de DNR et les utiliser comme variables d'optimisation, tout en fixant l'état des interrupteurs moins impactants (ON ou OFF) afin de réduire le nombre de variables binaires et d'accélérer le temps de calcul. Il serait intéressant d'étudier davantage l'impact du choix des OP, notamment, est-ce que le plan (*load, prod*) est suffisant, ou pourrait-on considérer d'autres dimensions ? De plus, dans quel type de problème ce type de démarche pourrait se généraliser ?

Après une phase initiale au cours de laquelle six PO ont été utilisés pour identifier les interrupteurs ayant un impact, la méthode de simplification a été testée sur deux PO pour un réseau réaliste de 2 588 bus. Les résultats ont montré que la méthode proposée améliorerait considérablement le temps de calcul, le rendant environ **177 fois plus rapide** dans le cas de l'OP2.

Nous avons donc proposé deux méthodes visant à réduire le temps de calcul du solveur. La méthode présentée dans ce chapitre a donné de meilleurs résultats que la méthode de réduction du réseau après avoir été testée sur un segment du réseau de distribution SRD.

Les travaux futurs devraient inclure des tests sur un plus grand nombre de DN avec un plus grand nombre d'OP et l'utilisation du MIP Start⁵ avec la solution obtenue par le DNR simplifié comme entrée pour vérifier si l'optimalité est atteinte. Si ce n'est pas le cas, le solveur doit être autorisé à l'atteindre. En outre, l'étude de cette vitesse améliorée pour d'autres applications de la DNR, telles que les scénarios en temps réel ou la reconfiguration dynamique, devrait également être effectuée.

Jusqu'à présent, nous avons proposé des méthodes d'optimisation en ne considérant qu'un unique point de fonctionnement (*load, prod*). Le résultat est une configuration unique réalisable qui est optimale pour cet unique point. L'objectif était de réduire le temps de calcul du solveur pour obtenir la solution. Dans le chapitre suivant, un cas généralisé sera étudié : le cas des charges et des productions dynamiques, et ses avantages par rapport à un point unique, ainsi que son effet sur le temps de calcul du solveur. Nous allons donc optimiser la configuration en considérant des courbes de charge prévues.

⁴Ou 132 interrupteurs si nous ne comptons que les interrupteurs « vraiment » utiles.

⁵Consiste en paires de variables et de valeurs pour aider le solveur à trouver une solution initiale.

9.7 Optimisation basée sur les courbes de charge

Dans les chapitres précédents, nous avons traité le cas des données de charge pour un unique point de fonctionnement, ce que l'on retrouve généralement dans la littérature DNR. Nous étions limités au scénario où nous disposions d'une valeur de puissance équivalente à un moment précis, définie pour chaque point du réseau. On peut considérer qu'il s'agit de charges et de productions statiques sur l'ensemble du réseau électrique. Nous avons proposé diverses améliorations permettant de réduire le modèle d'entrée afin de réduire le temps de calcul du solveur pour ce cas. Puisque nous avons la possibilité d'optimiser le réseau pour un point de fonctionnement en un temps acceptable par rapport au besoin industriel, nous allons généraliser l'optimisation en trouvant une configuration optimale étant donnée des courbes de charge. Cette configuration peut ne pas être optimale pour chaque point dans le temps, mais elle sera optimale pour la série temporelle considérée, et elle ne viole pas les contraintes associées à chaque temps dans l'ensemble donné.

9.7.1 Introduction

La plupart des approches de reconfiguration du réseau de distribution (DNR) proposées dans la littérature ne considèrent qu'un seul point de fonctionnement (OP). Cependant, puisque dans les chapitres précédents, nous avons proposé des méthodes pour réduire considérablement le temps de calcul du solveur pour un PO (qui est déjà difficile, comme nous l'avons vu dans le chapitre précédent en testant le modèle sur une agence SRD avec 2 588 sommets), nous nous demandons s'il est intéressant de travailler avec des courbes de charge/production. Dans le contexte de l'optimisation basée sur les courbes de charge, les charges variables dans le temps et la production variable de la génération distribuée sont prises en compte. L'idée ici est de choisir une configuration réalisable donnée pendant un intervalle de temps prédéfini (jour ou semaine) sur la base des prévisions de charge et de production, de sorte que les pertes au fil du temps soient minimisées.

D'autre part, les interrupteurs contenus dans les réseaux de distribution sont soit manuels, soit automatiques. Pour contrôler un interrupteur manuel, un agent doit se rendre physiquement sur le site pour le changer, ce qui entraîne un coût. De plus, un interrupteur a une durée de vie déterminée par le nombre de fois où il est actionné. Par conséquent, changer l'état d'un interrupteur a un coût. Il est donc crucial de trouver un moyen, en cas de présence d'une courbe de charge et de générations, de trouver une configuration réalisable qui respecte les contraintes pour l'intervalle de temps choisi. Cet intervalle de temps pourrait être long terme (par exemple une saison), ou bien plus court terme, par exemple lorsque des lignes sont indisponibles à cause de panne ou de travaux.

9.7.2 Contributions

Dans les chapitres précédents, nous avons traité le cas *Single Reconfiguration* où l'ensemble des temps est un singleton. Nous n'avons pas dit auparavant que l'ensemble des temps est un singleton, mais il peut être considéré comme tel. À ce singleton, une reconfiguration

est effectuée et une configuration optimale réalisable est donnée par le solveur en utilisant un Mixed Integer Quadratic Programming (MIQP).

Une généralisation peut maintenant être introduite lorsque nous disposons d'une fenêtre temporelle au lieu d'un seul instant (le cas où l'optimisation est appliquée aux courbes de charge et de production au lieu d'un tuple unique $(charge, génération)$). Soit $\tau = \{t_0, t_1, \dots, t_m\}$. Pour τ , qui peut aller de quelques heures (indisponibilité temporaire d'un ouvrage du réseau) à plusieurs mois (saison), on peut obtenir une configuration réalisable qui est optimale pour un temps t' dans τ et qui n'est pas optimale pour d'autres t dans τ sans violer les contraintes dans τ . Cette généralisation peut être appelée *Fixed Reconfiguration*. Si deux ou plusieurs configurations réalisables sont imposées pour être obtenues parmi τ , ce cas est appelé *Multiple reconfigurations avec contraintes opérationnelles*. Les contraintes opérationnelles indiquent ici le nombre maximal de reconfigurations réalisables ψ_{max} . Par exemple, pour l'ensemble des temps T , $\psi_{max} = 3$ dans la Fig. 9.4. En d'autres termes, nous obtiendrons trois configurations réalisables pour l'ensemble T .

Le troisième cas est appelé *reconfigurations multiples libres* lorsqu'aucune contrainte opérationnelle n'est imposée. En d'autres termes, à chaque instant t dans T , nous disposons d'une configuration optimale réalisable. Cette méthode de reconfiguration présente de nombreux inconvénients technologiques et économiques. En effet, la manipulation fréquente des interrupteurs manuels entraîne une augmentation des coûts de maintenance et d'exploitation. En outre, elle nécessite une surveillance et des ajustements plus fréquents du système par les opérateurs. D'autre part, elle nécessite des investissements importants dans des systèmes de contrôle avancés et dans l'acquisition de données en temps réel.

L'avantage de la reconfiguration fixe est que nous avons moins de variables binaires que dans le cas d'une reconfiguration libre sans limite du nombre de reconfigurations. Par conséquent, le temps de calcul nécessaire au solveur pour trouver la solution optimale est plus court. Mais l'inconvénient peut être vu dans le cas où nous avons une différence importante dans les charges ou les producteurs entre deux instants t_1 et t_2 . Dans ce cas, la topologie peut réduire les pertes de puissance pour t_1 mais pas pour t_2 . Le solveur choisira donc celle dont la fonction objective est la plus faible. Les limites de variation de tension et les autres contraintes doivent être respectées.

Nous présentons au chapitre 6 des modèles de reconfiguration fixe puis de reconfigurations multiples libres. Le modèle de reconfigurations multiples avec contraintes opérationnelles est ensuite introduit, avec des contraintes supplémentaires pour imposer un nombre maximum de configurations réalisables sur un ensemble d'instantanés pour le modèle de reconfigurations multiples libres.

9.7.3 Synthèse

Le chapitre 6 présente une étude sur l'optimisation basée sur les courbes de charge et de production pour le problème de reconfiguration du réseau de distribution (DNR). Une généralisation de la reconfiguration unique, appliquée dans les contributions précédentes pour réduire le temps de calcul du solveur, est étendue au contexte d'une fenêtre

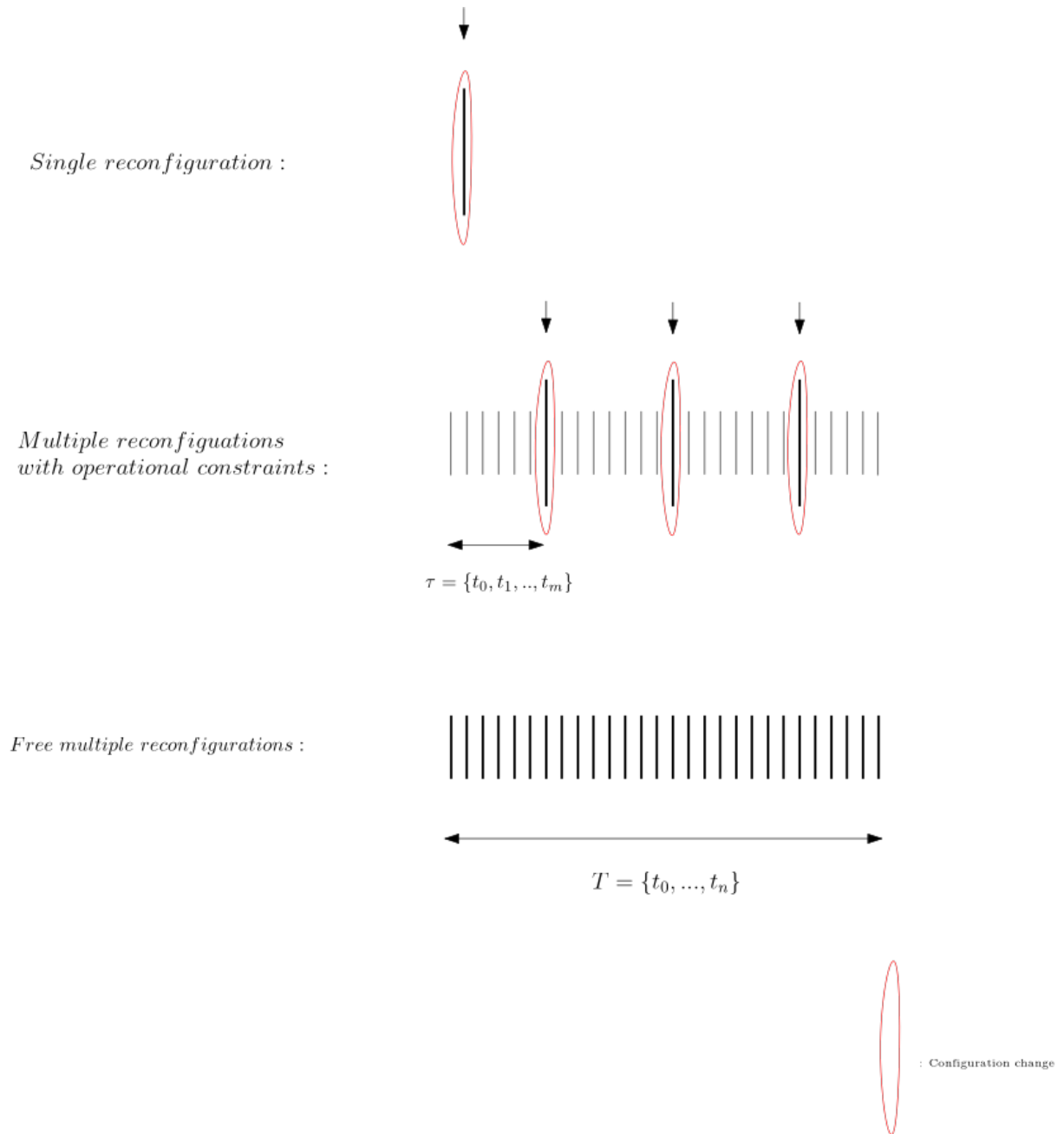


Figure 9.4: Optimisation dans le cas des courbes de charge et de production

temporelle. Le cas de la reconfiguration fixe, où l'objectif est de n'avoir qu'une seule reconfiguration parmi un ensemble d'instants, et le cas de la reconfiguration multiple libre, où le solveur peut changer la configuration réalisable à chaque instant, sont examinés. Une limitation du nombre maximal de configurations réalisables obtenues, appelée reconfigurations multiples avec contraintes opérationnelles, est également présentée. Une comparaison entre les reconfigurations multiples libres et les reconfigurations multiples avec contraintes opérationnelles est testée sur un réseau de bus IEEE-33 modifié dans différents scénarios de charge et de production pour chaque heure.

D'autre part, une comparaison entre le cas de la reconfiguration unique et le cas de la reconfiguration fixe est présentée pour comprendre les avantages de chacun. La comparaison est effectuée sur le réseau simplifié obtenu au chapitre précédent. La reconfiguration fixe nous permet d'obtenir une configuration réalisable qui respecte les contraintes pour tous les points de fonctionnement et qui est optimale pour un point spécifique. Nous introduisons ici le concept de Reconfiguration fixe pondérée, dont l'objectif est de donner de l'importance à l'ensemble des moments qui ne présentent pas d'amélioration en termes de pertes de puissance finales. Cette approche permet aux gestionnaires de réseaux de distribution (GRD) d'ajuster les pondérations en fonction des moments qui nécessitent une meilleure configuration réalisable.

Une autre contrainte semble être cruciale, lorsque le cas de la production d'électricité dépassée (production décentralisée) est présenté. La question est la suivante : que se passe-t-il si le solveur est incapable de trouver une configuration réalisable qui respecte toutes les contraintes à tout moment ? Le dépassement de la quantité de production peut être un obstacle à l'optimisation basée sur la courbe de charge. Le chapitre suivant fournira un moyen de traiter ce cas.

9.8 Réduction ponctuelle de la production décentralisée pour maintenir la stabilité de la tension

L'intégration progressive de la production distribuée donne lieu à d'importantes surproductions pendant certaines périodes dans les réseaux de distribution. Dans certains cas, cela peut conduire à une instabilité du réseau et à des fluctuations de tension, entraînant des dommages ou des pannes d'équipement. La prise en compte de ces instants où la surproduction d'une source ENR décentralisée peut aussi amener à configurer le réseau de façon non optimale sur la durée, la solution optimale étant en effet calculée en considérant la possibilité d'absorber cette production à tout instant comme une contrainte.

L'objectif de ce chapitre est d'atténuer les impacts des fortes intégrations de générations distribuées, tels que l'instabilité du réseau et les défis de stabilisation de la tension dans le cas de l'optimisation basée sur la courbe de charge pour le problème de reconfiguration du réseau de distribution (DNR).

9.8.1 Introduction

Dans le contexte de cette thèse, nous avons considéré la DNR comme un moyen de minimiser les pertes de puissance. Une reconfiguration unique peut être effectuée pour un point de fonctionnement unique constitué d'un tuple $(load, prod)$. Dans le chapitre précédent, une généralisation a été faite, et une optimisation basée sur la courbe de charge pour le problème de la DNR a été mise en œuvre.

Dans ce contexte, le cas de la reconfiguration fixe est intéressant à discuter et à étudier par rapport au cas de la reconfiguration unique (un seul point de fonctionnement) en raison de sa capacité à prendre en compte plusieurs fenêtres temporelles tout en fournissant une configuration réalisable qui respecte les contraintes électriques et opérationnelles pour chaque instant, mais qui est optimale pour un moment spécifique. En outre, le temps de calcul acceptable du solveur pour trouver la configuration réalisable le rend utilisable sur un réseau de GRD.

Dans le chapitre 7, nous poursuivrons l'optimisation basée sur la courbe de charge pour le problème DNR, en particulier avec le cas de la reconfiguration fixe, afin de discuter et de trouver une solution pour l'intégration élevée de la production décentralisée, où il est difficile ou impossible de trouver une configuration réalisable. La réduction de puissance peut être employée pour deux utilisations possibles : l'optimisation de la courbe de charge conformément au chapitre précédent, et le dimensionnement du réseau lors de l'installation d'une nouvelle infrastructure requise pour l'intégration d'un producteur décentralisé.

9.8.2 Contributions

Le chapitre 7 propose deux modèles basés sur le modèle de reconfiguration fixe présenté dans le chapitre précédent. Une seule configuration réalisable sera obtenue pour l'ensemble des instants. Le premier modèle proposé implique la relaxation des contraintes de tension. Le second modèle est le modèle de réduction de puissance, où la contribution réside dans

la linéarisation des contraintes qui détectent les violations de tension et quantifient la limitation à demander au producteur tout en imposant une limite maximale sur le nombre d'occurrences de réduction. En effet, en France, le GRD peut, suivant le contrat avec le producteur, imposer un nombre limité d'occurrences d'écèlement de la production. Les deux modèles s'inscrivent dans le contexte de la résolution de la contrainte de production excédentaire, comme mentionné dans l'introduction. L'efficacité de cette approche est évaluée à l'aide d'un petit réseau et d'une version modifiée du système de test IEEE 33-bus.

La relaxation des contraintes de tension permet bien entendu de trouver plus facilement une configuration réalisable qui satisfait les contraintes à tous les instants avec différentes conditions de charge et de production sans enfreindre les limites de tension, et bien entendu, l'espace de recherche étant strictement plus grand, on pourra y trouver des solutions réduisant les pertes. Sans cet assouplissement, l'optimisation peut nécessiter différentes configurations pour différents moments afin de gérer les fluctuations, ce qui implique de multiples reconfigurations. Cela convient à notre cas, où nous étudions le cas de la reconfiguration fixe dans le cadre d'une optimisation basée sur la charge à l'aide du problème DNR. La relaxation de la tension permet à une configuration unique de faire face à diverses situations, telles qu'une charge de pointe ou une production décentralisée élevée, par exemple, sans que les limites de tension ne soient dépassées. Notons que cela se traduirait, dans l'exploitation d'un réseau, par une demande d'écèlement de production auprès des producteurs concernés par le relâchement des contraintes.

L'autre modèle présenté dans le chapitre 7 est le modèle de réduction de la puissance. Il est essentiel de déterminer la quantité de puissance réduite qui résulte du dépassement

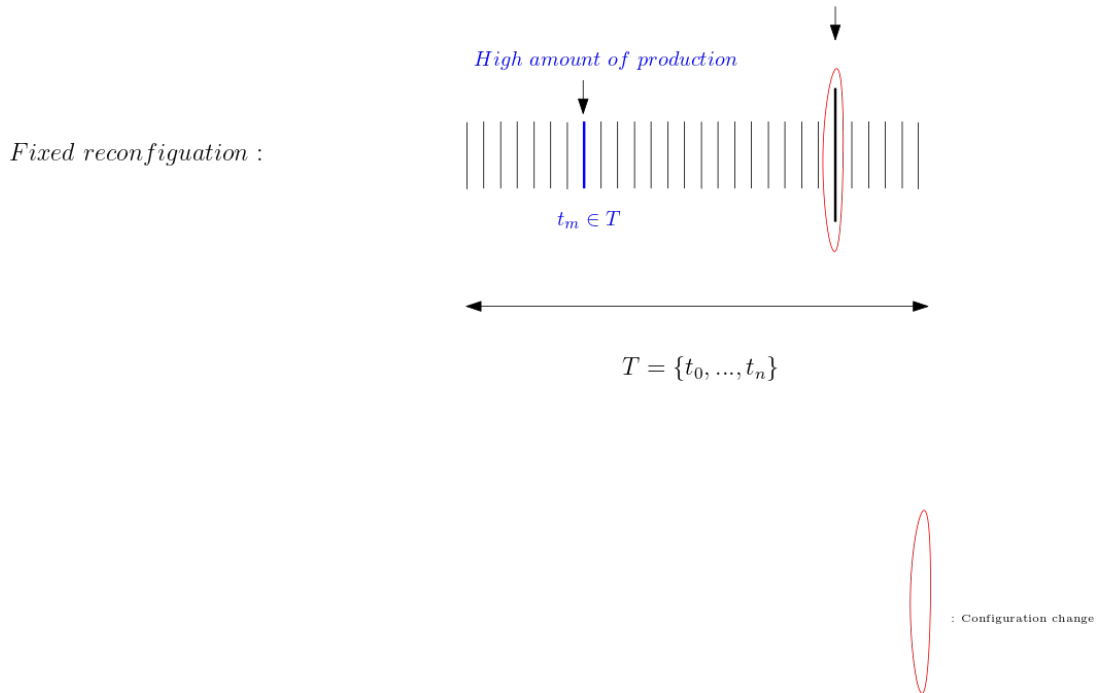


Figure 9.5: Cas d'une reconfiguration fixe avec un taux de production élevé à un instant donné

des limites de tension. Le concept de ce modèle consiste à relaxer les contraintes de la loi des nœuds. L'objectif est de déterminer la quantité de réduction de production nécessaire pour respecter les limites de tension dans le cas d'une forte intégration de la production distribuée.

9.8.3 Synthèse

Ce chapitre résout le problème de l'impossibilité pour le solveur de trouver une configuration réalisable qui satisfasse les contraintes à tous les instants dans le modèle de reconfiguration fixe des contraintes d'optimisation basées sur la charge d'une part, et permet de réduire les pertes en évitant que des contraintes posées par la production décentralisée ne réduisent l'espace des solutions. Les contraintes proposées sont testées sur un réseau de bus IEEE-33 modifié dans le cadre de divers scénarios de production. Les résultats obtenus sont conformes au fait que le réseau devrait réduire sa production excédentaire à un point pour lequel la limite de tension est respectée. D'autres études pourraient être menées dans les cas où le coût de la réduction est inclus dans la fonction objectif.

9.9 Conclusions et perspectives

Cette thèse aborde différents aspects des méthodologies de reconfiguration des réseaux de distribution (DNR) dans le contexte de l'optimisation des pertes de puissance pour les réseaux de distribution. Le problème DNR, connu comme NP-complet en raison de l'espace de recherche qui n'est pas borné, est résolu à l'aide de la programmation par contraintes en proposant une programmation quadratique en nombres entiers mixtes (MIQP). Le problème initial était de réduire le temps de calcul du solveur lorsque l'entrée du DNR est constituée de réseaux de distribution à grande échelle. Les différentes méthodologies dans ce contexte sont appliquées dans le cas d'un point de fonctionnement unique (*load, prod*) où le temps de calcul du solveur reste important. La première méthodologie est un algorithme appliqué au graphe dans l'entrée de la programmation quadratique en nombres entiers mixtes (MIQP) utilisée afin de réduire l'espace de recherche de la solution pour le solveur commercial utilisé (Cplex, Gurobi). Cette méthode permet de réduire le temps de calcul du solveur en utilisant deux types de réduction de réseau : le premier proposé par cette thèse, et le second issu de la littérature.

Après cette contribution, une méthode d'élimination des interrupteurs à faible impact dans les réseaux de distribution est présentée. L'objectif est de trouver les interrupteurs les plus impactants en termes de DNR et de les utiliser comme variables d'optimisation, tout en définissant l'état des interrupteurs moins impactants comme leur état initial et en l'utilisant comme données dans le MIQP. Cette méthode comporte une phase d'identification des commutateurs les plus impactants. La phase d'identification est réalisée en exécutant le DNR (formulé comme un MIQP) de manière séquentielle sur un ensemble de points de fonctionnement initiaux, puis, sur la base d'un coefficient défini pour chaque commutateur, chacun est classé comme ayant le plus d'impact ou le moins d'impact dans la résolution du problème du DNR. Après avoir testé cette méthode sur un réseau réaliste de 2 588 bus, les résultats ont montré que la méthode proposée améliorerait considérablement le temps de calcul, le rendant environ 177 fois plus rapide dans le cas d'un seul point de fonctionnement. Dans la perspective de cette contribution, les travaux futurs devraient inclure une procédure pour déterminer les points de fonctionnement initiaux les plus représentatifs qui seront utilisés pour classer les différents commutateurs.

Ensuite, nous présentons une généralisation du cas de la reconfiguration unique, qui a été utilisée pour traiter le problème de la réduction du temps de calcul du solveur, au cas de courbes de charges. Une étude de l'optimisation basée sur la courbe de charge pour le problème DNR est présentée et une comparaison entre les différents cas possibles est effectuée. Ensuite, le cas de *Fixed Reconfiguration* est choisi comme la meilleure option en termes d'optimisation de la courbe de charge. Il consiste à trouver une configuration unique réalisable qui est optimale pour un instant spécifique et qui respecte les contraintes des autres instants sans être optimale pour ces derniers.

A ce stade, et dans le contexte d'une forte intégration de la production décentralisée, le réseau peut perdre sa stabilité. En outre, conformément à notre thèse, le solveur peut ne pas être en mesure de trouver une configuration réalisable qui satisfasse toutes les contraintes d'instant en présence d'une production excédentaire à des instants spécifiques, de plus certaines productions décentralisées peuvent être dimensionnantes pour la con-

figuration, et empêcher de trouver des solutions réduisant les pertes à cause d'instantanés localisés de surproduction. La réduction de la puissance est une solution dont l'objectif est de réduire la quantité de puissance excédentaire de manière à respecter la limite de tension maximale. Cela se fait en relâchant les contraintes d'équilibre de puissance pour quantifier la quantité de puissance réduite.

Bibliography

- [AAE22] Ahmed S Abbas, Adel A Abou El-Ela, and Ragab A El-Sehiemy. “Maximization approach of hosting capacity based on uncertain renewable energy resources using network reconfiguration and soft open points”. In: *International Transactions on Electrical Energy Systems* 2022.1 (2022), p. 2947965.
- [Abi+19] Oludare Isaac Abiodun, Aman Jantan, Abiodun Esther Omolara, Kemi Victoria Dada, Abubakar Malah Umar, Okafor Uchenwa Linus, Humaira Arshad, Abdullahi Aminu Kazaure, Usman Gana, and Muhammad Ubale Kiru. “Comprehensive review of artificial neural network applications to pattern recognition”. In: *IEEE access* 7 (2019), pp. 158820–158846.
- [ACT21] Jennie Andersen, Brice Chardin, and Mohamed Tribak. “Clustering to the Fewest Clusters Under Intra-Cluster Dissimilarity Constraints”. In: *2021 IEEE 33rd International Conference on Tools with Artificial Intelligence (ICTAI)*. 2021, pp. 209–216. DOI: 10.1109/ICTAI52525.2021.00036.
- [AJB19] MohamadAli Amini, Alireza Jalilian, and Milad Rahimi Pour Behbahani. “Fast network reconfiguration in harmonic polluted distribution network based on developed backward/forward sweep harmonic load flow”. In: *Electric Power Systems Research* 168 (2019), pp. 295–304.
- [Ali+16] Abdelkrim Ali Zazou, Emmanuel Grolleau, Emilie Chevrier, Pascal Richard, Jean-Paul Gaubert, and Ladjel Bellatreche. “Power distribution network reconfiguration based on min-cost flow problem”. In: *2016 IEEE 14th International Conference on Industrial Informatics (INDIN)*. IEEE. 2016, pp. 286–291.
- [Ali17] Abdelkrim Ali Zazou. “Conception d’un outil d’optimisation dynamique du schéma d’exploitation du réseau de distribution d’électricité de SRD”. PhD thesis. ISAE-ENSMA, 2017.
- [AM15] Hamed Ahmadi and José R Martí. “Minimum-loss network reconfiguration: A minimum spanning tree problem”. In: *Sustainable Energy, Grids and Networks* 1 (2015), pp. 1–9.
- [Ant+21] Degarege Anteneh, Baseem Khan, Om Prakash Mahela, Hassan Haes Alhelou, and Josep M Guerrero. “Distribution network reliability enhancement and power loss reduction by optimal network reconfiguration”. In: *Computers & Electrical Engineering* 96 (2021), p. 107518.

- [Bar+21] Constantin Barbulescu, Stefan Kilyeni, Cosmin Oros, Alex Bittenbinder, and Marin Salinschi. “Heuristic and Metaheuristic Techniques based Distribution Network Reconfiguration. Case study: IEEE 33 Bus System”. In: *2021 International Conference on Applied and Theoretical Electricity (ICATE)*. 2021, pp. 1–6. DOI: 10.1109/ICATE49685.2021.9465030.
- [Bar21] Sanjoy Baruah. “Feasibility analysis of conditional dag tasks is co-npnp-hard”. In: *Proceedings of the 29th International Conference on Real-Time Networks and Systems*. 2021, pp. 165–172.
- [BCW24] Shahab Bahrami, Yu Christine Chen, and Vincent W. S. Wong. “Dynamic Distribution Network Reconfiguration With Generation and Load Uncertainty”. In: *IEEE Transactions on Smart Grid* 15.6 (2024), pp. 5472–5484. DOI: 10.1109/TSG.2024.3404859.
- [Bor12] Alberto Borghetti. “A mixed-integer linear programming approach for the computation of the minimum-losses radial configuration of electrical distribution networks”. In: *IEEE Transactions on Power Systems* 27.3 (2012), pp. 1264–1273.
- [Bou+10] Aggelos S Bouhouras, Georgios T Andreou, Dimitris P Labridis, and Anastasios G Bakirtzis. “Selective automation upgrade in distribution networks towards a smarter grid”. In: *IEEE Transactions on Smart Grid* 1.3 (2010), pp. 278–285.
- [BV04] Stephen P Boyd and Lieven Vandenbergh. *Convex optimization*. Cambridge university press, 2004.
- [BW89] Mesut E Baran and Felix F Wu. “Network reconfiguration in distribution systems for loss reduction and load balancing”. In: *IEEE Transactions on Power delivery* 4.2 (1989), pp. 1401–1407.
- [Cav17] Ellen Marianne Bernal Cavalheiro. “Otimização das configurações de redes de distribuição de energia elétrica com fontes distribuídas”. PhD thesis. Dissertação de mestrado a ser apresentado a faculdade de engenharia elétrica ..., 2017.
- [CCS05] Ji-Pyng Chiou, Chung-Fu Chang, and Ching-Tzong Su. “Variable scaling hybrid differential evolution for solving network reconfiguration of distribution systems”. In: *IEEE transactions on power systems* 20.2 (2005), pp. 668–674.
- [ČJ20] Rade Čadenović and Damir Jakus. “Maximization of distribution network hosting capacity through optimal grid reconfiguration and distributed generation capacity allocation/control”. In: *Energies* 13.20 (2020), p. 5315.
- [CRP08] Edgar Manuel Carreno, Rubén Romero, and Antonio Padilha-Feltrin. “An efficient codification to solve distribution network reconfiguration for loss reduction problem”. In: *IEEE Transactions on Power Systems* 23.4 (2008), pp. 1542–1551.
- [Dah97] Geir Dahl. “An introduction to convexity, polyhedral theory and combinatorial optimization”. In: *University of Oslo, Department of Informatics* (1997).

- [Dia+20] Ibrahim Mohamed Diaaeldin, Shady HE Abdel Aleem, Ahmed El-Rafei, Almoataz Y Abdelaziz, and Ahmed F Zobaa. “Enhancement of hosting capacity with soft open points and distribution system reconfiguration: Multi-objective bilevel stochastic optimization”. In: *Energies* 13.20 (2020), p. 5446.
- [Die12] Reinhard Diestel. *Graph Theory: Springer Graduate Text GTM 173*. Vol. 173. Reinhard Diestel, 2012.
- [DT68] Hermann W Dommel and William F Tinney. “Optimal power flow solutions”. In: *IEEE Transactions on power apparatus and systems* Unknown.10 (1968), pp. 1866–1876.
- [Esm+19] Saeid Esmaeili, Amjad Anvari-Moghaddam, Shahram Jadid, and Josep M Guerrero. “Optimal simultaneous day-ahead scheduling and hourly reconfiguration of distribution systems considering responsive loads”. In: *International Journal of Electrical Power & Energy Systems* 104 (2019), pp. 537–548.
- [Fat16] Hassan Fathabadi. “Power distribution network reconfiguration for power loss minimization using novel dynamic fuzzy c-means (dFCM) clustering based ANN approach”. In: *International Journal of Electrical Power & Energy Systems* 78 (2016), pp. 96–107.
- [GCS22] Cassio Gerez, Eduardo Coelho Marques Costa, and Alfeu J Sgurezi Filho. “Distribution network reconfiguration considering voltage and current unbalance indexes and variable demand solved through a selective bio-inspired metaheuristic”. In: *Energies* 15.5 (2022), p. 1686.
- [GKE14] Zeinab Ghofrani-Jahromi, Mostafa Kazemi, and Mehdi Ehsan. “Distribution switches upgrade for loss reduction and reliability improvement”. In: *IEEE Transactions on Power Delivery* 30.2 (2014), pp. 684–692.
- [GKL01] Zong Woo Geem, Joong Hoon Kim, and Gobichettipalayam Vasudevan Loganathan. “A new heuristic optimization algorithm: harmony search”. In: *simulation* 76.2 (2001), pp. 60–68.
- [GLG22] Luis A Gallego Pareja, Jesús M López-Lezama, and Oscar Gómez Carmona. “A mixed-integer linear programming model for the simultaneous optimal distribution network reconfiguration and optimal placement of distributed generation”. In: *Energies* 15.9 (2022), p. 3063.
- [Glo86] Fred Glover. “Future paths for integer programming and links to artificial intelligence”. In: *Computers & operations research* 13.5 (1986), pp. 533–549.
- [GLS81] Martin Grötschel, László Lovász, and Alexander Schrijver. “The ellipsoid method and its consequences in combinatorial optimization”. In: *Combinatorica* 1 (1981), pp. 169–197.
- [Gom+05] F Vanderson Gomes, Sandoval Carneiro, Jose Luiz R Pereira, Marcio Pinho Vinagre, Paulo Augusto Nepomuceno Garcia, and Leandro Ramos Araujo. “A new heuristic reconfiguration algorithm for large distribution systems”. In: *IEEE Transactions on Power systems* 20.3 (2005), pp. 1373–1378.

- [Guo+22] Lingxu Guo, Zhigang Huang, Jing Wang, Guangyao Yu, Yanzhen Zhou, Zhiqiang Chong, and Zhenbin Li. “Distribution Network Reconfiguration Algorithms: A Comparative Study”. In: *2022 IEEE 5th International Conference on Electronics Technology (ICET)*. 2022, pp. 472–478. DOI: 10.1109/ICET55676.2022.9824709.
- [Gura] Gurobi. *heuristics*. URL: <https://www.gurobi.com/documentation/current/refman/heuristics.html>.
- [Gurb] Gurobi. *Mipgap*. URL: <https://www.gurobi.com/documentation/current/refman/mipgap2.html>.
- [HD23] Pratik Harsh and Debapriya Das. “A Simple and Fast Heuristic Approach for the Reconfiguration of Radial Distribution Networks”. In: *IEEE Transactions on Power Systems* 38.3 (2023), pp. 2939–2942. DOI: 10.1109/TPWRS.2023.3256136.
- [Hel+21] Ahmed M Helmi, Raffaele Carli, Mariagrazia Dotoli, and Haitham S Ramadan. “Efficient and sustainable reconfiguration of distribution networks via metaheuristic optimization”. In: *IEEE Transactions on Automation Science and Engineering* 19.1 (2021), pp. 82–98.
- [HH23] Tong Han and David J. Hill. “Learning-Based Topology Optimization of Power Networks”. In: *IEEE Transactions on Power Systems* 38.2 (2023), pp. 1366–1378. DOI: 10.1109/TPWRS.2022.3170083.
- [HSB21] Ebtsam A Hamza, Bishoy E Sedhom, and Ebrahim A Badran. “Impact and assessment of the overvoltage mitigation methods in low-voltage distribution networks with excessive penetration of PV systems: A review”. In: *International Transactions on Electrical Energy Systems* 31.12 (2021), e13161.
- [HT15] Hassan Hijazi and Sylvie Thiébaux. “Optimal distribution systems reconfiguration for radial and meshed grids”. In: *International Journal of Electrical Power & Energy Systems* 72 (2015), pp. 136–143.
- [Jia+24] Changxu Jiang, Zheng Lin, Chenxi Liu, Feixiong Chen, and Zhenguo Shao. “MADDPG-Based Active Distribution Network Dynamic Reconfiguration with Renewable Energy”. In: *Protection and Control of Modern Power Systems* 9.6 (2024), pp. 143–155. DOI: 10.23919/PCMP.2023.000283.
- [JL91] GB Jasmon and LHCC Lee. “Distribution network reduction for voltage stability analysis and loadflow calculations”. In: *International Journal of Electrical Power & Energy Systems* 13.1 (1991), pp. 9–13.
- [JSP12] Rabih A Jabr, Ravindra Singh, and Bikash C Pal. “Minimum loss network reconfiguration using mixed-integer convex programming”. In: *IEEE Transactions on Power systems* 27.2 (2012), pp. 1106–1115.
- [JV12] Saeed Jazebi and Behrooz Vahidi. “Reconfiguration of distribution networks to mitigate utilities power quality disturbances”. In: *Electric Power Systems Research* 91 (2012), pp. 9–17.
- [Kar] Nour Karnib. *Realistic Network*. URL: https://forge.lias-lab.fr/realistic_network.

- [Kas+98] MA Kashem, GB Jasmon, Azah Mohamed, and M Moghavvemi. “Artificial neural network approach to network reconfiguration for loss minimization in distribution networks”. In: *International Journal of Electrical Power & Energy Systems* 20.4 (1998), pp. 247–258.
- [KBS22] Reza Khorram-Nia, Bahman Bahmani-Firouzi, and Mohsen Simab. “Optimal scheduling of reconfigurable microgrids incorporating the PEVs and uncertainty effects”. In: *IET Renewable Power Generation* 16.16 (2022), pp. 3531–3543.
- [KFS20] M Khajevand, A Fakharian, and M Sedighizadeh. “Stochastic joint optimal distributed generation scheduling and distribution feeder reconfiguration of microgrids considering uncertainties modeled by copula-based method”. In: *Iranian Journal of Electrical and Electronic Engineering* 16.3 (2020), pp. 371–392.
- [Kho+09] HM Khodr, J Martinez-Crespo, MA Matos, and J Pereira. “Distribution systems reconfiguration based on OPF using Benders decomposition”. In: *IEEE Transactions on Power Delivery* 24.4 (2009), pp. 2166–2176.
- [Kho+18] A Khodabakhsh, G Yang, S Basu, E Nikolova, M Caramanis, T Lianes, and E Pountourakis. “A Submodular Approach for Electricity Distribution Network Reconfiguration”. In: *Proceedings of the 51st Hawaii International Conference on System Sciences (HICSS)*. 2018.
- [Kou+16] Nikolaos C Koutsoukis, Dimitris O Siagkas, Pavlos S Georgilakis, and Nikos D Hatziargyriou. “Online reconfiguration of active distribution networks for maximum integration of distributed generation”. In: *IEEE Transactions on Automation Science and Engineering* 14.2 (2016), pp. 437–448.
- [Lav+11] Marina Lavorato, John F Franco, Marcos J Rider, and Rubén Romero. “Imposing radiality constraints in distribution system optimization problems”. In: *IEEE Transactions on Power Systems* 27.1 (2011), pp. 172–180.
- [Lei+17] Shunbo Lei, Yunhe Hou, Feng Qiu, and Jie Yan. “Identification of critical switches for integrating renewable distributed generation by dynamic network reconfiguration”. In: *IEEE Transactions on Sustainable Energy* 9.1 (2017), pp. 420–432.
- [LJD16] Zhechao Li, Saeed Jazebi, and Francisco De Leon. “Determination of the optimal switching frequency for distribution system reconfiguration”. In: *IEEE Transactions on Power Delivery* 32.4 (2016), pp. 2060–2069.
- [LS23] Hossein Lotfi and Ali Asghar Shojaei. “A dynamic model for multi-objective feeder reconfiguration in distribution network considering demand response program”. In: *Energy Systems* 14.4 (2023), pp. 1051–1080.
- [Mah+21a] Meisam Mahdavi, Hassan Haes Alhelou, Amir Bagheri, Sasa Z. Djokic, and Ricardo Alan Verdú Ramos. “A Comprehensive Review of Metaheuristic Methods for the Reconfiguration of Electric Power Distribution Systems and Comparison With a Novel Approach Based on Efficient Genetic Algorithm”. In: *IEEE Access* 9 (2021), pp. 122872–122906. DOI: 10.1109/ACCESS.2021.3109247.

- [Mah+21b] Meisam Mahdavi, Hassan Haes Alhelou, Nikos D. Hatziargyriou, and Francisco Jurado. “Reconfiguration of Electric Power Distribution Systems: Comprehensive Review and Classification”. In: *IEEE Access* 9 (2021), pp. 118502–118527. DOI: 10.1109/ACCESS.2021.3107475.
- [MB75] A Merlin and H Back. “Search for a minimal-loss operating spanning tree configuration in an urban power distribution system”. In: *Proc. 5th Power System Computation Conf., Cambridge, UK*. 1975, pp. 1–18.
- [Min08] Michel Minoux. *Programmation mathématique. Théorie et algorithmes*. Lavoisier, 2008.
- [MK22] Manuel Sathyajith Mathew and Mohan Lal Kolhe. “Performance Modelling of Renewable Energy Systems Using kNN Algorithm for Smart Grid Applications”. In: *2022 7th International Conference on Smart and Sustainable Technologies (SpliTech)*. 2022, pp. 1–4. DOI: 10.23919/SpliTech55088.2022.9854321.
- [Mos+17] Mustafa Mosbah, Salem Arif, Ridha Djamel Mohammedi, and Abdelhafid Hellal. “Optimum dynamic distribution network reconfiguration using minimum spanning tree algorithm”. In: *2017 5th International Conference on Electrical Engineering-Boumerdes (ICEE-B)*. IEEE. 2017, pp. 1–6.
- [NA14] Adarsh Nagarajan and Raja Ayyanar. “Application of minimum spanning tree algorithm for network reduction of distribution systems”. In: *2014 North American Power Symposium (NAPS)*. IEEE. 2014, pp. 1–5.
- [Nar+92] Koichi Nara, Atsushi Shiose, Minoru Kitagawa, and Toshihisa Ishihara. “Implementation of genetic algorithm for distribution systems loss minimum re-configuration”. In: *IEEE Transactions on Power systems* 7.3 (1992), pp. 1044–1051.
- [Otu+23] Duku Otuo-Acheampong, Ghamgeen Izat Rashed, Amoh Mensah Akwasi, and Hussain Haider. “Application of Optimal Network Reconfiguration for Loss Minimization and Voltage Profile Enhancement of Distribution System Using Heap-Based Optimizer”. In: *International Transactions on Electrical Energy Systems* 2023.1 (2023), p. 9930954.
- [Ram+05] E Romero Ramos, A Gómez Expósito, J Riquelme Santos, and F Llorens Iborra. “Path-based distribution network modeling: application to reconfiguration for loss reduction”. In: *IEEE Transactions on power systems* 20.2 (2005), pp. 556–564.
- [Rao+10] Rayapudi Srinivasa Rao, Sadhu Venkata Lakshmi Narasimham, Manyala Ramalinga Raju, and A Srinivasa Rao. “Optimal network reconfiguration of large-scale distribution system using harmony search algorithm”. In: *IEEE Transactions on power systems* 26.3 (2010), pp. 1080–1088.
- [Rao+12] R Srinivasa Rao, Kumudhini Ravindra, K Satish, and SVL Narasimham. “Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation”. In: *IEEE transactions on power systems* 28.1 (2012), pp. 317–325.

- [Raz+22] Seyed-Mohammad Razavi, Hamid-Reza Momeni, Mahmoud-Reza Haghi-fam, and Sadegh Bolouki. “Multi-Objective Optimization of Distribution Networks via Daily Reconfiguration”. In: *IEEE Transactions on Power Delivery* 37.2 (2022), pp. 775–785. DOI: 10.1109/TPWRD.2021.3070796.
- [Rib+18] Luiz Carlos Ribeiro, Joseph PO Schumann Minami, Benedito Donizeti Bonatto, Paulo Fernando Ribeiro, and Antonio Carlos Zambroni de Souza. “Voltage control simulations in distribution systems with high penetration of PVs using the OpenDSS”. In: *2018 Simposio Brasileiro de Sistemas Eletricos (SBSE)*. IEEE. 2018, pp. 1–6.
- [RJ23] Milad Rahimipour Behbahani and Alireza Jalilian. “Reconfiguration of harmonic polluted distribution network using modified discrete particle swarm optimization equipped with smart radial method”. In: *IET Generation, Transmission & Distribution* 17.11 (2023), pp. 2563–2575.
- [RKB22] Shafin Rahman, Salman Khan, and Nick Barnes. “Polarity Loss: Improving Visual-Semantic Alignment for Zero-Shot Detection”. In: *IEEE Transactions on Neural Networks and Learning Systems* (2022), pp. 1–13. DOI: 10.1109/TNNLS.2022.3184821.
- [RRR10] E Romero-Ramos, J Riquelme-Santos, and J Reyes. “A simpler and exact mathematical model for the computation of the minimal power losses tree”. In: *Electric Power Systems Research* 80.5 (2010), pp. 562–571.
- [Sal21] Surender Reddy Salkuti. “Feeder reconfiguration in unbalanced distribution system with wind and solar generation using ant lion optimization”. In: *International Journal of Advanced Computer Science and Applications* 12.3 (2021).
- [Sch+05] Hernan Prieto Schmidt, Nathan Ida, Nelson Kagan, and João Carlos Guaraldo. “Fast reconfiguration of distribution systems considering loss minimization”. In: *IEEE Transactions on Power systems* 20.3 (2005), pp. 1311–1319.
- [SE68] Glenn W Stagg and Ahmed H El-Abiad. “Computer methods in power system analysis”. In: (*No Title*) (1968).
- [SGR06] Harold Salazar, Ramón Gallego, and Rubén Romero. “Artificial neural networks and clustering techniques applied in the reconfiguration of distribution systems”. In: *IEEE Transactions on Power Delivery* 21.3 (2006), pp. 1735–1742.
- [SH89] Dariush Shirmohammadi and H Wayne Hong. “Reconfiguration of electric distribution networks for resistive line losses reduction”. In: *IEEE Transactions on Power Delivery* 4.2 (1989), pp. 1492–1498.
- [Sil+21] Christoffer L Bezão Silveira, Alejandra Tabares, Lucas Teles Faria, and John F Franco. “Mathematical optimization versus Metaheuristic techniques: A performance comparison for reconfiguration of distribution systems”. In: *Electric Power Systems Research* 196 (2021), p. 107272.
- [SL03] Ching-Tzong Su and Chu-Sheng Lee. “Network reconfiguration of distribution systems using improved mixed-integer hybrid differential evolution”. In: *IEEE Transactions on power delivery* 18.3 (2003), pp. 1022–1027.

- [Spi+12] Vitaly Spitsa, Xuanchang Ran, Reynaldo Salcedo, Juan F Martinez, Resk Ebrahim Uosef, Francisco De Leon, Dariusz Czarkowski, and Zivan Zabar. “On the transient behavior of large-scale distribution networks during automatic feeder reconfiguration”. In: *IEEE Transactions on Smart Grid* 3.2 (2012), pp. 887–896.
- [Sul+16] Beenish Sultana, MW Mustafa, U Sultana, and Abdul Rauf Bhatti. “Review on reliability improvement and power loss reduction in distribution system via network reconfiguration”. In: *Renewable and sustainable energy reviews* 66 (2016), pp. 297–310.
- [TH12] Joshua A Taylor and Franz S Hover. “Convex models of distribution system reconfiguration”. In: *IEEE Transactions on Power Systems* 27.3 (2012), pp. 1407–1413.
- [Thu+18] L. Thurner, A. Scheidler, F. Schäfer, J. Menke, J. Dollichon, F. Meier, S. Meinecke, and M. Braun. “pandapower — An Open-Source Python Tool for Convenient Modeling, Analysis, and Optimization of Electric Power Systems”. In: *IEEE Transactions on Power Systems* 33.6 (Nov. 2018), pp. 6510–6521. ISSN: 0885-8950. DOI: 10.1109/TPWRS.2018.2829021.
- [TL18] Dawit F Teshome and Kuo Lung Lian. “Comprehensive mixed-integer linear programming model for distribution system reconfiguration considering DGs”. In: *IET Generation, Transmission & Distribution* 12.20 (2018), pp. 4515–4523.
- [Tou+15] Sellé Touré, Emmanuelle Vanet, Raphaël Caire, and Yvon Besanger. “Assessment methods for the targeted reconfiguration in distribution networks”. In: *2015 IEEE Eindhoven PowerTech*. IEEE. 2015, pp. 1–6.
- [Tri21] Mohamed Tribak. “Estimation and Prediction of Renewable Energy Production and Consumption of an Electricity Distribution Network”. PhD thesis. ISAE-ENSMA Ecole Nationale Supérieure de Mécanique et d’Aérotechnique-Poitiers, 2021.
- [TYF13] Lei Tang, Fang Yang, and Xianrong Feng. “A novel method for distribution system feeder reconfiguration using black-box optimization”. In: *2013 IEEE Power & Energy Society General Meeting*. IEEE. 2013, pp. 1–5.
- [War49] James B Ward. *Equivalent Circuits in Power System Studies*. Purdue University, 1949.
- [Wen+18] Juan Wen, Yanghong Tan, Lin Jiang, and Kejun Lei. “Dynamic reconfiguration of distribution networks considering the real-time topology variation”. In: *IET Generation, Transmission & Distribution* 12.7 (2018), pp. 1509–1517.
- [Xu+16] Lizhou Xu, Ruofa Cheng, Zhihua He, Jibang Xiao, and Huazhu Luo. “Dynamic reconfiguration of distribution network containing distributed generation”. In: *2016 9th International Symposium on Computational Intelligence and Design (ISCID)*. Vol. 1. IEEE. 2016, pp. 3–7.

- [Zar+24] Peyman Zare, Seyed Jalal Seyed Shenava, Hosein Shayeghi, Iraj Faraji Davoudkhani, and Amir Mohammadian. “Unveiling Mountaineering Team-Based Optimization Algorithm for Performance Enhancement of Radial Distribution”. In: *2024 11th Iranian Conference on Renewable Energy and Distribution Generation (ICREDG)*. Vol. 11th. 2024, pp. 1–7. DOI: 10.1109/ICREDG61679.2024.10607831.
- [ZfZ07] Dong Zhang, Zhengcai Fu, and Liuchun Zhang. “An improved TS algorithm for loss-minimum reconfiguration in large-scale distribution systems”. In: *Electric power systems research* 77.5-6 (2007), pp. 685–694.
- [Zha+18] HF Zhai, M Yang, B Chen, and N Kang. “Dynamic reconfiguration of three-phase unbalanced distribution networks”. In: *International Journal of Electrical Power & Energy Systems* 99 (2018), pp. 1–10.
- [Zhe+23] Han Zheng, Christopher Kang, Gokul Subramanian Ravi, Hanrui Wang, Kanav Setia, Frederic T. Chong, and Junyu Liu. “SnCQA: A hardware-efficient equivariant quantum convolutional circuit architecture”. In: *2023 IEEE International Conference on Quantum Computing and Engineering (QCE)*. Vol. 01. 2023, pp. 236–245. DOI: 10.1109/QCE57702.2023.00034.

APPLICATION OF OPTIMIZATION IN REGIONAL DISTRIBUTION NETWORK RECONFIGURATION

Abstract:

In the domain of operations research, this thesis's subject consists of optimizing electrical networks (specifically, distribution networks) in terms of power losses. The main addressed problem is the Distribution Network Reconfiguration (DNR) problem and several variations of the problem. The DNR problem is widely studied in the literature and is an effective approach for Distribution System Operators (DSOs) to optimize their networks in terms of power loss due to Joule heat. With the high integration of distributed generation (decentralized generation), reconfiguring the network's operation scheme becomes crucial to improving the economics for these DSOs. The optimization model consists of a Mixed Integer Quadratic Programming (MIQP) problem, where the distribution network is represented as a graph, which serves as an input for this MIQP. The binary variables consist of the state of each switch (1 or 0) along with the continuous variables representing the flows in each line. The objective function is the sum of power losses for the configuration selected by the solver. This thesis first reduces the solver's computational time when the considered loads and generations are static (at one single point in time). It proposes a network reduction method, where the input graph in the MIQP is reduced to decrease the solution's search space for the solver. With the same goal, a method for eliminating low-impact switches is proposed and tested on an SRD agency network. This method involves proposing a set of operating points for load and generation coefficients across the entire network, where the MIQP is launched sequentially. Then, the low-impact switches in the MIQP are fixed as data, while the most impactful switches remain as variables. The results showed that the proposed method greatly improved computational time, making it roughly 177 times faster in the case of a given operating point independent of the initial ones. After these attempts to reduce the solver's computational time in the static case, a generalization is proposed, where the goal is to optimize power losses over a time horizon. This is referred to as multiple reconfiguration under operational constraints. Then, the case of free reconfigurations is explored, where no operational constraints are imposed. This case allows the solver to change the solution at each time point, but this approach faces many technological and economic barriers. Finally, in the case of high production integration, where no solution can handle it, power curtailment is introduced to curtail power in excess and maintain a feasible solution.

Keywords: (Quadratic programming, Operations research, Electric power systems–Electric losses, Electric power systems–Control)

APPLICATION DE L'OPTIMISATION À LA RECONFIGURATION DU RÉSEAU DE DISTRIBUTION RÉGIONAL

Résumé :

Dans le domaine de la recherche opérationnelle, le sujet de cette thèse consiste à optimiser les réseaux électriques (en particulier les réseaux de distribution) en termes de pertes de puissance. Le principal problème abordé est le problème de la reconfiguration des réseaux de distribution (DNR) et plusieurs variations de ce problème. Le problème DNR est largement étudié dans la littérature et constitue une approche efficace pour les gestionnaires de réseaux de distribution (DSO) afin d'optimiser leurs réseaux en termes de perte de puissance due à la chaleur Joule. Avec la forte intégration de la production distribuée (production décentralisée), la reconfiguration du schéma d'exploitation du réseau devient cruciale pour améliorer l'économie de ces GRD. Le modèle d'optimisation consiste en un problème de programmation quadratique en nombres entiers mixtes (MIQP), où le réseau de distribution est représenté sous la forme d'un graphe, qui sert d'entrée à ce MIQP. Les variables binaires sont l'état de chaque interrupteur (1 ou 0) et les variables continues représentent les flux dans chaque ligne. La fonction objective est la somme des pertes de puissance pour la configuration sélectionnée par le solveur. Cette thèse réduit d'abord le temps de calcul du solveur lorsque les charges et les générations considérées sont statiques (à un seul moment dans le temps). Elle propose une méthode de réduction du réseau, où le graphe d'entrée du MIQP est réduit pour diminuer l'espace de recherche de la solution pour le solveur. Dans le même but, une méthode d'élimination des commutateurs à faible impact est proposée et testée sur un réseau d'agences SRD. Cette méthode consiste à proposer un ensemble de points de fonctionnement pour les coefficients de charge et de production sur l'ensemble du réseau, où le MIQP est lancé de manière séquentielle. Ensuite, les commutateurs à faible impact dans le MIQP sont fixés en tant que données, tandis que les commutateurs les plus importants restent en tant que variables. Les résultats ont montré que la méthode proposée améliorerait considérablement le temps de calcul, le rendant environ 177 fois plus rapide dans le cas d'un point de fonctionnement donné indépendant des points initiaux. Après ces tentatives de réduction du temps de calcul du solveur dans le cas statique, une généralisation est proposée, où l'objectif est d'optimiser les pertes de puissance sur un horizon temporel. On parle alors de reconfiguration multiple sous contraintes opérationnelles. Ensuite, le cas des reconfigurations libres est exploré, lorsqu'aucune contrainte opérationnelle n'est imposée. Ce cas permet au solveur de modifier la solution à chaque point dans le temps, mais cette approche se heurte à de nombreux obstacles technologiques et économiques. Enfin, dans le cas d'une forte intégration de la production, qu'aucune solution ne peut gérer, la réduction de la puissance est introduite pour réduire la puissance excédentaire et maintenir une solution réalisable.

Mots clés : (Programmation quadratique, Recherche opérationnelle, Reconfiguration (informatique), Réseaux électriques (énergie)–Pertes d'énergie, Réseaux électriques (énergie)–Régulation, Réseaux de distribution d'électricité, Programme quadratique à nombre entier mixte (MIQP))