Faculdade de Engenharia da Universidade do Porto

Benefits of Coordinating Distribution Network Reconfiguration with Distributed Generation and Energy Storage Systems

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Resumo

O problema de integrar produção distribuída (DG) renovável em sistemas de distribuição de energia está a tornar-se bastante crítico devido a razões técnicas, económicas e ambientais. Atualmente, existe um consenso global de que a integração de recursos de origem renovável – RESs, é altamente necessária para ter em conta o aumenta da procura de eletricidade e reduzir a pegada de carbono global de produção de energia. Contudo, a integração em larga escala de DG baseada em RES muitas vezes coloca desafios de ordem técnica no sistema, desde a perspetiva da estabilidade, fiabilidade e qualidade de energia. Isto deve-se porque a integração de RESs introduz uma expressiva variabilidade e incerteza no sistema de distribuição que faz com que a operação, planeamento e controlo se tornem complexos. Consequentemente, um esforço ao nível da integração é provável que seja suportado por certas tecnologias das redes inteligentes *smart grids* e conceitos que tenham a capacidade de aumentar a flexibilidade de todo o sistema de distribuição. Neste contexto, a integração de sistemas distribuídos de armazenamento de energia (DESSs) em conjunto com DGs, juntamente com a capacidade de comutação da rede e/ou reforço da rede, pode aumentar significativamente a flexibilidade do sistema, e por isso, beneficia a produção RES.

Este trabalho apresenta um novo método para quantificar os impactos associados a DESS assim como a comutação da rede e/ou reforço ao nível de integração de produção renovável no sistema. Para executar esta análise, dois modelos foram desenvolvidos, um modelo de programação linear inteira mista (MILP) e um modelo baseado em Algoritmos Genéticos (GA). Estes modelos têm em consideração o reforço na rede de distribuição e/ou comutação em coordenação com a integração de tecnologias DGs baseadas em RES e DESS.

As metodologias propostas são testadas nos sistemas de 16 e 33-nós do IEEE. Os resultados da análise mostram a capacidade de comutação/reforço da rede e a integração de DESS em suportar significativamente a integração em larga escala de DGs renováveis.

Palavras-Chave

Algoritmo Genético (acrónimo em inglês, GA), Comutação da Rede, Produção Distribuída (acrónimo em inglês, DG), Programação Linear Inteira Mista (acrónimo em inglês, MILP), Reforço da Rede, Sistemas Renováveis de Energia (acrónimo em inglês, RESs), Sistemas Distribuídos de Armazenamento de Energia (acrónimo em inglês, DESS).

Abstract

The issue of integrating renewable distributed generation (DG) in power distribution systems is becoming critical because of technical, economic and environmental reasons. Nowadays, there is a global consensus that integrating renewable energy sources—RESs, is highly needed to meet an increasing demand for electricity and reduce the overall carbon footprint of energy production. However, large-scale integration of RES-based DGs often poses a number of technical challenges in the system, from stability, reliability and power quality perspectives. This is because integrating RESs introduces significant operational variability and uncertainty to the distribution system, making operation, planning and control rather complicated. Hence, such a high level integration effort is likely to be supported by certain smart-grid technologies and concepts that have the capability to enhance the flexibility of the entire distribution system. Framed in this context, the integration of distributed energy storage systems (DESSs) jointly with DGs, along with the network's switching capability and/or network reinforcement, significantly improves the flexibility of the system, thereby increasing chances of accommodating large-scale RES power.

This work presents a novel method to quantify the impacts of installing DESS as well as network switching and/or reinforcement on the level of renewable power integrated in the system. To carry out this analysis, two models are developed, mixed integer linear programming (MILP) and Genetic Algorithm (GA) based models. These models take into account the distribution network reinforcement and/or switching in coordination with integrating RES-based DGs and DESS technologies.

The proposed methodologies are tested on 16- and 33-node systems. The results show the capability of network reinforcement/switching and DESS integration in significantly supporting large-scale integration of renewable DGs.

Keywords

Genetic Algorithms (GA), Network Switching, Distributed energy storage systems, Distributed Generation, Mixed Integer Linear Programming (MILP), Network Reinforcement, Renewable Energy Sources (RESs), Energy Storage Systems (ESS).

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Virtus Unita Fortius Agit

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Acronyms and Nomenclature

Acronyms

AC	Alternating Current
AHP	Analytic Hierarchic Process
ACA	Ant Colony Algorithm
ABC	Artificial Bee Colony
AIS	Artificial Immune System
ARMA	Auto Regression Moving average
DESS	Distributed Energy Storage System
DQPSO	Decimal coded Quantum Particle Swarm Optimization
DOE	Department of Energy
DC	Direct Current
DG	Distributed Generation
DSR	Distribution Systems Reconfiguration
EWD	Edge Window Decoder
EDS	Electrical Distribution Systems
EWS	Energy Management Strategy
ENS	Energy Not Supplied
ESS	Energy Storage System
EU	European Union
EA	Evolutionary Algorithm
EPSO	Evolutionary Particle Swarm Optimization
FNSGA	Fast Nondominated Sorting Guided Genetic Algorithm
GA	Genetic Algorithm
HSA	Harmony Search Algorithm
HOMER	Hybrid Optimization Model for Electric Renewables
IEA	International Energy Agency
MILP	Mixed Integer Linear Program
MINLP	Mixed Integer Non Linear Programming
MISOCP	Mixed-Integer Second-Order Cone Programming
MPSO	Modified Particle Swarm Optimization

MACS	Multiagent Control System
MMP	Multi-objective Mathematical Programming
NPV	Net Present Value
NLMIP	Non-Linear Mixed Integer Programming
OPF	Optimal Power Flow
PSO	Particle Swarm Optimization
RHC	Receding Horizon Control
RES	Renewable Energy Sources
SA	Scenario Analysis
TS	Tabu Search
NSGA-II	Non-dominated Sorting Genetic Algorithm II
TSC	Total Supply Capability
UVDA	Uniform Voltage Distribution based constructive Reconfiguration Algorithm
UPS	Uninterruptible Power Supply
US	United States
Vaccine-AIS	Vaccine-enhanced Artificial Immune System

Nomenclature

A. Sets/Indices

i/Ω^i	Index/set of buses
$g/\Omega^g/\Omega^{DG}$	Index/set of generators/DGs
k/Ω^k	Index/set of branches
s/Ω^s	Index/set of scenarios
t/Ω^t	Index/set of planning stages
w/Ω^w	Index/set of snapshots
$\varsigma/\Omega^\varsigma$	Index/set of substations

B. Parameters

$ER_g^N, ER_g^E, ER_\varsigma^{SS}$	Emission rates of new and existing DGs, and energy purchased, respectively (tCO_2e/MWh)
$IC_{g,i}, IC_k, IC_{es,i}$	Investment cost of DG, line and energy storage, respectively (M€)
$LT_g, LT_k, LT_{tr}, LT_{es}$	Lifetimes of DG, distribution line, transformer and energy storage system, respectively (years)
MC_{es}, MC_{tr}	Maintenance cost of storage per year (M€)
MC_g^N, MC_g^E	Maintenance costs of new and existing DGs (M€/yr)
MC_k^N, MC_k^E	Maintenance cost of new and existing line (M€/yr)
$OC_{g,i,s,w,t}^N, OC_{g,i,s,w,t}^E$	Operation cost of unit energy production by new and existing DGs (€/MWh)
$\lambda_{s,w,t}^{CO_2e}$	Price of emissions (€/tons of CO_2 equivalent)
$\lambda_{s,w,t}^\varsigma$	Price of electricity purchased (€/MWh)
ρ_s, π_w	Probability of scenario *s* and weight (in hours) of snapshot group *w*
$\upsilon_{s,w,t}$	Penalty for unserved power (€/MW)
$\eta_{ch,es}$	Charging efficiency

μ_{es}	Scaling factor

C. Variables

$\delta_{i,s,w,t}$	Unserved power at node *i*
$D^{i}_{s,w,t}$	Active power demand at node *i*
$P^{N}_{g,i,s,w,t}, P^{E}_{g,i,s,w,t}$	Active power produced by new and existing DGs
$P^{SS}_{\varsigma,s,w,t}$	Active power imported from grid
$u_{g,i,t}, u_{k,t}$	Utilization variables of existing DG and lines
$x_{g,i,t},\ x_{es,i,t}, x_{k,t}$	Investment variables for DG, storage systems and distribution lines, respectively
$\varphi_{k,s,w,t}$	Losses associated to each feeder
$E_{es,i,s,w,t}$	Reservoir level of ESS
$I^{dch}_{es,i,s,w,t}, I^{ch}_{es,i,s,w,t}$	Discharging/charging indicator variables
$P^{dch}_{es,i,s,w,t}, P^{ch}_{es,i,s,w,t}$	Discharged/charged power
$x_{tr,ss,t}$	Transformer investment variable

D. Functions

EC^{SS}_{t}	Expected cost of energy purchased from upstream
$ENSC_{t}$	Expected cost of unserved power
$EmiC^{DG}_{t}$	Expected emission cost of DG power production
$EmiC^{N}_{t}, EmiC^{E}_{t}$	Expected emission cost of power production using new and existing DGs, respectively
$EmiC^{SS}_{t}$	Expected emission cost of purchased power
$InvC^{DNS}_{t}, MntC^{DNS}_{t}$	NPV investment/maintenance cost of DNS components
$InvC^{DG}_{t}, MntC^{DG}_{t}, EC^{DG}_{t}$	NPV investment/maintenance/expected energy cost of DGs, respectively
$InvC^{LN}_{t}, MntC^{LN}_{t}$	NPV investment/maintenance cost of a line
$InvC^{ES}_{t}, MntC^{ES}_{t}$	NPV investment/maintenance cost of ESS

Chapter 1

Introduction

1.1 – Background

Driven by technical, economic, environmental and structural factors, the integration of Renewable Energy Sources (RESs) in power systems has been increasing steadily. Furthermore, global concerns such as climate change, energy dependence and security and other related issues are forcing policy makers and states to introduce new energy policies (RES policies, in particular) that support the development and utilization of RESs. The favorable agreement of states to curb emissions and mitigate climate change is also expected to further accelerate RES integration in power systems (particularly, at a distribution level). The level of Distributed Generation (DG) deployed in distribution network systems follows an upward trend, and there is a general consensus that DGs will immensely contribute to the efforts of addressing a multitude of the aforementioned global and local concerns including collective (and/or individual) RES integration targets set forth by different entities.

The availability of several matured DG technologies and their decreasing cost trends, along with constraints in the construction of new transmission lines, increased customers' demand for highly reliable electricity etc. has been encouraging considerable investments in DGs (particularly, renewable types such as wind and solar power). However, large-scale integration of DGs in distribution network systems may sometimes bring technical problems to the system such as voltage rise issues. Such challenges need to be resolved if the system is to support the integration and full (efficient) utilization of massive DG power. One way is to properly allocate DGs in the system. The purpose of DG placement (allocation) is to find the optimal location and size of DGs (generally non-conventional energy sources) in the system, close to the end consumers.

In particular, large-scale integration of RES-based DGs often poses a number of technical challenges in the system from the stability, reliability and power quality perspective. This is because integrating RESs introduces significant operational variability and uncertainty to the distribution system, making operation, planning and control rather complicated.

Hence, such a high level integration effort is likely to be supported by certain smart-grid technologies and concepts that have the capability to enhance the flexibility of the entire distribution systems. Energy Storage Systems (ESSs) can play a vital role integrating variable energy sources. In addition, Reconfiguration of Distribution System (RDS) can be very important because RDS can considerably enhance the flexibility of the system and voltage profiles, thereby increasing chances of accommodating large-scale RES power.

1.2 – Problem Statement

RESs make a crucial part of the solution for environmental sustainability; hence, they will play an important role in power systems. The integration of RESs should, in principle, reduce the risk of fuel price volatility and geopolitical pressures and ensure that these do not pose a significant impact on the overall public welfare. However, large-scale penetration of RESs will necessarily involve a process of adapting and changing the existing infrastructure because of their intrinsic characteristics, such as intermittency and variability. The growing need for intermittent RESs, in conjunction with the electrical mix changes in the long-term, will probably affect the distribution and transmission systems. In this context, a change in power generation options, resulting from a high contribution of RESs, may require network grid updates. Regulatory agencies are heavily committed to increase RES integration, not only due to environmental but also technical and economic reasons. The main challenge with most of RESs is their inherent variability and uncertainty, making operation, control and planning very complicated. DG penetration increases the variation of voltage and current in the network. Hence, increasing DG penetration may have a negative or a positive impact depending on various factors such as the size of the system and the loads type, requiring modeling and simulations to assess its impact. If not properly planned, this may lead to an uncertain increase in the feeders' power flows, resulting in network congestion and increased losses in the network. However, the integration of ESS along with RESs has become one of the most viable solutions to facilitate the increased penetration of DG resources. Energy storage systems level the mismatch between renewable power generation and demand. This is because these devices store energy during periods of low electricity demand (price) or high RES power production, and then release it during periods of peak demand and low RES production. Therefore, in addition to their technical support to the system, ESSs bring substantial benefits for end-users and DG owners through reliability and power quality improvement as well as cost reduction. Besides, ESSs are being developed and applied in power grids to cope with a number of issues such as smoothing the energy output from RESs, improving the stability of the electrical system, etc. ESSs also increase savings during peak hours and minimize the impact of intermittent generation sources, leading to a more efficient management of the integrated system. Despite the high capital costs of many ESS technologies, their deployment in distribution systems is in the upward trend. Cost-cutting and the strong need of integrating RES-based DGs is expected to push the demand for the simultaneous deployment of ESSs in distribution network systems. In other words, distributed ESSs will increase dramatically in the years to come. Hence, proper planning of such systems is crucial for a healthy operation of the system as a whole. This relates to developing appropriate mathematical models and algorithms that lead to the optimal placement, timing and sizing of DGs and ESSs in the system, which is one of the problems addressed in this thesis.

Electrical distribution systems are interconnected by switches but predominantly operated radially. These switches are often used for emergency purposes such as to evade load curtailment during fault cases. However, the system can be reconfigured to find the best topology that minimizes power losses in the system and improve operational performance. This in turn improves the flexibility in the system, which may help the system to accommodate (absorb) more variable power. Investigating the capability of network switching and/or expansion along with ESS deployment in RES integration level is another problem addressed in this thesis.

1.3 – Objectives

This thesis aims to achieve the following goals:

- To carry out a comprehensive state-of-the-art literature review on the subject areas of distribution network reconfiguration, DG and ESS integrations, which forms a basis for defining the problem addressed in this thesis;
- To develop mathematical models for jointly optimizing distribution network reconfiguration, optimal placement, timing and sizing of ESS and RES-based DGs considering uncertainty and variability inherent to such problems;
- To carry out case studies and perform relevant analysis of results;
- To analyse the effects of distribution reconfiguration in the distribution networks;
- To carry out quantitative and qualitative analysis in relation to the influences optimal sizing, location and timing of DGs and ESSs along with distribution network reconfiguration on relevant system variables in the distribution network.

1.4 - Methodology

The work in this thesis involves both qualitative and quantitative analysis regarding the impact of joint integration ESSs, network switching (reconfiguration) and reinforcement on the level of DG integration (particularly, focusing on RESs). In order to achieve the objectives, set in this thesis, a set of different mathematical simulation models are developed.

In order to solve the proposed objectives were created two optimization models. The first proposed optimization model is coded by multi-objective Stochastic Mixed Integer Linear Program (S-MILP) to a planning horizon of three years and solved with GAMS, considering the operational variability and uncertainty of variable power resources along with reconfiguration and energy storage systems.

Also, a second optimization model proposed is coded by a GA and solved using the MatPower (package of MATLAB) optimal power flow (OPF). GA considers: 1) one snapshot of the distribution system to solve reconfiguration and 2) one snapshot of the distribution system to solve reconfiguration with optimal size and location of DGs. To reach at best reconfiguration of the distribution network GA will raffle the connected branches (1 or 0), proceed to resolution of OPF with the configuration given and keep the OPF costs DG's placement and size is done at the same time by raffling the nodes were DGs are connected by the two-third theory. Size of DGs is done by takin an interval between 1 and 4 MW and raffle an integer number between that interval. A comparison between the base case and the best case given by GA is done, comparing reconfiguration only and reconfiguration with placement and size of DGs.

The objective for the two methods is minimization of costs. In the case of S-MILP the total costs of the system (objective function) is composed of Net Present Value (NPV) of five cost terms: 1) investment costs, 2) costs of maintenance, 3) cost of energy in the system, 4) cost of unserved power and 5) total emission costs. For GA model the costs are given by the optimal power flow, consequently the cost of energy provided to the demand is minimized.

1.5 - Thesis Structure

The thesis is organized as follows. Chapter 2 presents a literature review of relevant works on the subject area of the thesis. A theoretical overview of the genetic algorithm, along with the descriptions of the entire solution process, is presented in Chapter 3. The stochastic mathematical models developed in this thesis are described in Chapter 4. Case studies, results and discussions are presented in Chapter 5. Chapter 6 gathers the relevant conclusions drawn from the numerical results, and shows directions for future work.

Chapter 2

Literature Review

2.1 – Chapter Overview

This chapter presents an extensive review of related works on subject area of distribution systems planning particularly focusing on the problems of distribution network reconfiguration, distribution generation and energy storage allocation and sizing in distribution network systems. The reviewed works are largely structured based on the methodologies used to solve the aforementioned problems.

2.2 – Distribution System Reconfiguration

2.2.1 – Motivation of DSR

Electrical distribution systems link high voltage transmission systems and the end-consumers. They are often designed in a slightly meshed manner but normally operated in a radial configuration because of a number of reasons such as reduction of costs, uncomplicated coordination of protection systems, reduced occurrence of faults, better control power flows and voltage profile. Because of such reasons, maintaining the radial topology of the network systems is very critical. The reasons further explain the need for optimizations of distribution network systems to obtain the optimal radial topology [1].

For the system to operate on a permanent basis, it is desirable to increase its efficiency and reduce its operating costs. One way to achieve this is by minimizing losses [2]. Some techniques used to reduce system losses are increasing the voltage level, cable replacement, installation of condensers and/or distribution systems reconfiguration (DSR). Among these techniques, the reconfiguration is the most attractive for the electricity distribution company because it allows the use of resources that already exist in the system. Consequently, DSR can be implemented by changing the status of the switches that connect/disconnect the branches of the system, in order to obtain a radial topology [3]–[20]. Reconfiguration can be done for numerous reasons, as in normal or emergency operation conditions.

In [21] authors show that losses in distribution network systems constitute more than 75% of the total system losses, contributing to a 40% of the total cost incurred to deliver power and 80% of customer reliability. The losses are also classified as technical and non-technical losses. Non-technical losses include unauthorized line tapping, meter ampering, inaccurate meter reading, subsidies, unmetered public lighting etc. They can be reduced by monitoring, creating awareness, installing accurate metering devices etc. Technical losses occur due to flow of electric current. They cause economic damage.

The DSR problems can be formulated as single-objective or multi-objective optimizations. In such optimization problems, there are two objectives that stand out, minimization of losses, especially in mono-objective approaches, and in multi-objective approaches besides the previous target, also operating costs minimization and maximization of the profit. It should be noted that in the multi-objective approach, the objective functions can be conflicting, in which case, the optimum solution is the result of a trade-off between multiple objectives [2].

Due to its explicit benefits (mentioned earlier), there has been a growing number of literature on the DSR problem over the past years, and it still remains an actual working topic. Generally, the goal of network reconfiguration is not only to reduce power losses but also to improve voltage profile, network reliability and economic operations. Therefore, DSR aims to find the best topology of the system taking into account power losses, energy demand, operational performance and other relevant determining factors.

Based on the solution techniques applied to solve DSR problems, the literature on DSR can be broadly classified into two categories: 1) mathematical techniques; 2) heuristic and metaheuristic techniques [22].

2.2.2 – Mathematical Solution Techniques in DSR

In the literature, a number of exact techniques have been widely employed to solve DSR problems, such mixed-integer linear programming (MILP) [3], [8] mixed-integer second-order cone programming (MISOCP) [4], analytic hierarchic process (AHP) [9]. Paterakis *et al.* in [3] propose a MILP DSR optimization model, which is formulated as a multi-objective mathematical programming (MMP) problem. The objective function constitutes the minimization of the active power losses and the minimization of commonly used reliability indices, which are explicitly treated within the MILP formulation. In [4], Chen *et al.* presents the assessment of distribution network total supply capability (TSC) value modelled as a MISOCP optimization problem. Gupta *et al.* [8] suggest a new MILP model which combines power and reliability objectives into a single objective function. A real time configuration based on load rate analysis is proposed by Pfitscher *et al.* [9]. AHP is applied in a multicriteria decision making and analyzing of parallelism of feeders using Euler's discretization method to make sure that the reconfiguration outcome does not violate radiality constraints.

The mathematical techniques have been less commonly used mainly due to computational limitations. However, this paradigm has been changing with increased processing capability of computing machines in addition to the new processing styles that have been developed recently such as cloud computing. Heuristics and metaheuristics techniques have been employed in recent years. Several of these techniques are combined in order to exploit the best characteristic of each technique.

2.2.3 - Heuristic and Metaheuristic Solution Techniques in DSR

The mathematical computational complexity of the DSR problem (mainly due to its combinatorial, non-convex and nonlinear nature) has led to the extensive use of heuristic and metaheuristic techniques in the literature by researchers. Some of these methods which have been widely used to solve the aforementioned problem include genetic algorithm (GA) [5], [7], [10], [11], [16], [18], [19], particle swarm optimization (PSO) [14] and others. A new non dominated sorting guided GA (FNSGA) has been used to solve a multi-objective problem by Eldurssi and O'Connell [5]. For automated reconfiguration, an enhanced GA has been suggested by Duan et al. [7], with the aim of determining the optimal network configuration that leads to the minimum power losses and/or the maximum system reliability. Torres et al. [10] uses a GA for solving a DSR problem with purpose of minimizing real power losses while satisfying several system operating constraints. A codification strategy based on the edge window decoder (EWD) encoding technique that only leads to radial configurations has been employed. Even if the DSR problem has been formulated as a MILP optimization in [8], authors use GA to obtain the best compromising radial operating configuration. Cebrian and Kagan [16] address the reconfiguration of distribution networks considering power quality indices by formulating such a problem as non-linear mixed integer programming optimization, which is then solved by an evolutionary algorithm (EA).

In [11], the DSR optimization is formulated as a single objective problem, encompassing only the active power losses minimization. To find the optimal or near-optimal configuration each candidate configuration is analyzed in two steps. First, the candidate topology is assessed whether or not it is a valid radial configuration. Second, if the first condition is fulfilled, a power flow module is run from which steady state variables are determined. Meshed heuristic algorithm has been developed by Mena and García [13] to solve the reconfiguration problem with an objective function of network losses minimization. Niknam and Farsani [14] have combined a hybrid EA with a self-adaptive discrete PSO to determine the statuses of sectionalizing switch numbers, and a self-adaptive binary PSO to determine the statuses of tie switches. This way, the distribution network is optimally reconfigured maintaining its radial topology. Abul'Wafa [15] propose a heuristic approach, embedded in a load flow algorithm that gives precise branch currents, node voltages and system power losses. Sahoo and Prasad [17] consider voltage stability as the objective function, and the resulting DSR problem is solved using a fuzzy GA. Mendoza *et al* [18] minimize losses via reconfiguration, which is solved using a generic GA. The GA technique is based on the creation of an initial population of feasible individuals. A fuzzy mutated GA is proposed by Prasad *et al*. [19] for reconfiguration of distribution systems with a new chromosome representation of the network and a fuzzy mutation control.

2.3 – Distributed Generation and Distribution System Reconfiguration

2.3.1 – Overview of Distributed Generation

As mentioned in the previous section, DSR can be characterized as changing the statuses of various switches that connect/disconnect the branches of the system in order to obtain a radial topology which improves overall system performance and efficiency.

The subsequent topology, yet, depends on many input parameters and needs to be updated on a daily, monthly, or periodic basis to adjust to the changes in the system operating condition. With increased penetration of variable renewable Distributed Generation (DG), one is more likely to experience constantly changing system conditions. As a result, the need for network reconfiguration increases because this enhances the flexibility of the system, which is useful to cope with operational variations.

The purpose of distributed generation (DG) placement is to connect distributed generating units, generally based on non-conventional energy sources, at end consumers. According to the International Energy Agency (IEA), there are five key factors that have significantly increased interest in distributed generations [23]: 1) development in DG technologies, 2) constraints on construction of new transmission lines, 3) increased customer demand for highly reliable electricity, 4) electricity market liberalization and 5) concerns about climate change.

Distributed generation (DG) implies the deployment of small generation units (from 1kW to 1MW) connected to distribution network and close to the end-consumers [24]. In addition, unlike conventional electrical networks that have unidirectional power flow, the introduction of DG leads to a bidirectional power flow.

Technical, economic and environmental advantages, as well as the disadvantages of DG integrations are presented [23],[24].

DG is classified in renewable energy sources (RES) and non-renewable energy sources. RES-based DGs are classified as photovoltaic (PV), wind, hydro, geo-thermal, tidal and bio fuel. The non RES-based DG includes the diesel generator[23]. Some of the advantages of integrating DG's [21], [25] are summarized in Figure 2.1. Distribution networks have been designed to handle unidirectional power flow. The introduction of DGs can have positive or negative impact on the distribution network systems [23], [24]. The main negative impacts include:

- Integration of DGs can result in overvoltage issues. This is not a problem when DG is connected to a system with low voltage issues. However, for weakly loaded systems, DG integration may result in high voltage problems interfering with standard voltage regulation practices. RES based DGs can especially worsen the voltage profile due to their intermittent nature.
- The impact on protection co-ordination given that the power grids are designed to operate for unidirectional power flow.
- The impact on harmonics as a result of integrating RES based DGs, which often require power electronic interfaces, major sources of harmonics injected in the system.
- The impact on reactive power management can be an issue with DG units which are incapable of providing reactive power. Hence, if DG units are not properly located and sized, they can have negative effects on the system. When connected to the network, various DG technologies can lead to high levels of reliability and security issues [24], [23], [26].

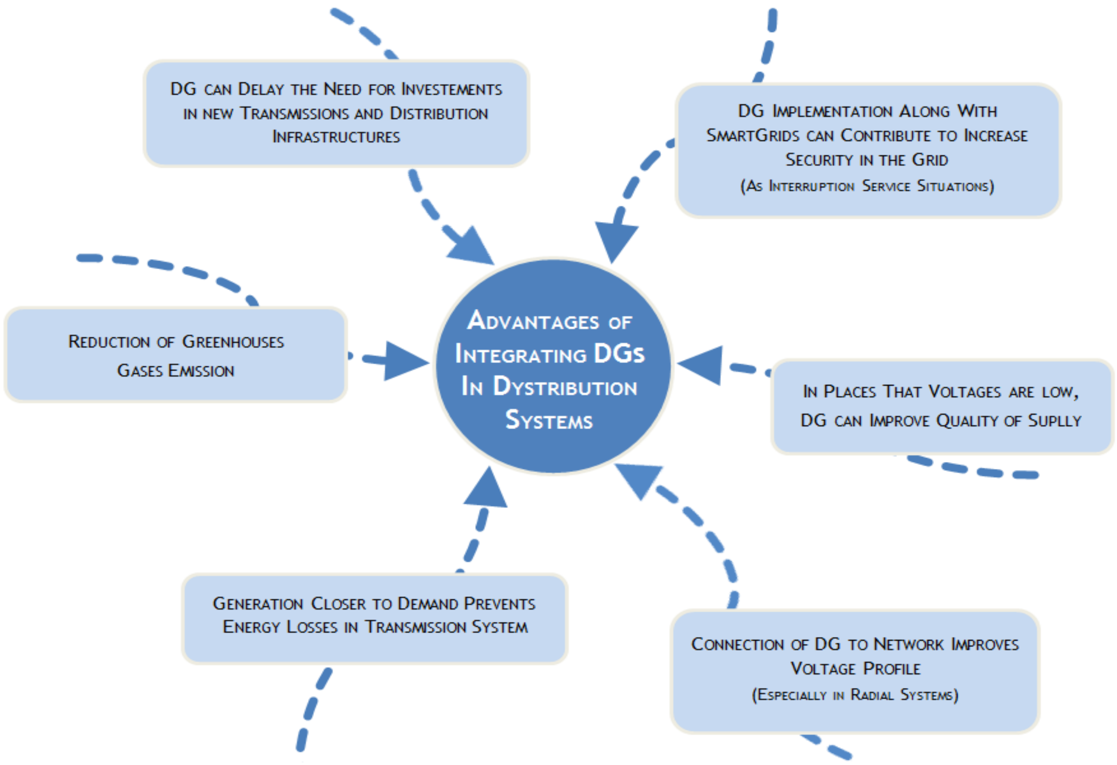

Figure 2.1 - The main advantages of integrating Distributed Generators in the distribution system (adapted from [24]).

Despite the steady growth of DG systems in recent years, there are still certain barriers (technical, economic, regulatory) that restrict progress toward a new paradigm of electric networks [24].

2.3.2 - DG Allocation in Distribution Systems—A Literature Review

Georgilakis and Hatziargyriou [27] present a review on the models, the methods and future research of optimal DG placement in electrical distribution systems. Typically, the DG allocation is a complex optimization problem that deals with the optimal planning of DGs in existing distribution networks while respecting a number of technical, economic and environmental constraints. Such an optimization work should lead to the optimal location and size as well as the installation timing of DGs. The DG planning optimization problem is usually difficult to solve using traditional mathematical methods because it is a nonlinear, non-convex and combinatorial problem.

A number of approaches and methods have been proposed in the literature for simultaneously restructuring of distribution network, and placement and sizing of DGs. Majority of the previous works in this regard aim to reduce active power losses and improve the voltage profile [28], [29]. The solution methods applied for solving the problems can be broadly classified as 1) mathematical, 2) heuristic and meta-heuristic 3) hybrid types [21].

Mathematical techniques including MILP [30], [31], MISOCP [32] and multi-period optimal power flow (MP-OPF) [33] have been employed in the literature to resolve the DG planning problem. Haghighat and Zeng [30] propose a method to find a robust radial network topology with minimum losses of a distribution system considering uncertainty in load and renewable generation. The resulting problem is formulated in a MILP two-stage optimization framework.

The DSR problem aims to minimize losses under uncertain load and generation. The problem has been decomposed in a master-slave structure. Ghamsari *et al.* [32] have developed a MISOCP mathematical model to analyze the possibility and economics of an hourly reconfiguration in the presence of renewable energy resources. The objective function of the resulting problem is to minimize daily network losses via applying hourly reconfigurations, formulated as a MISOCP problem which is then solved using the MOSEK solver. Capitanescu *et al.* [33] proposes a multi-period OPF approach for assessing the improvement of DG hosting capacity of distribution systems by applying static or dynamic reconfiguration, together with active network management schemes. Muñoz-Delgado *et al.* [31] report a MILP optimization model whose objective is to minimize the net present value of the total cost including the costs related to investment, maintenance, production, losses, and unserved energy. The costs of energy losses are modeled by a piecewise linear approximation. Tahboub e*t al.* [6] use MINLP to formulate the DSR and a fuzzy C-means clustering algorithm is used to obtain representative centroids from annual DG and power demand profiles

In the heuristic and meta-heuristic solution techniques category, a uniform voltage distribution based constructive reconfiguration algorithm (UVDA) [34], GA [35]-[37], modified particle swarm optimization (MPSO) [38], decimal coded quantum particle swarm optimization (DQPSO) [39], PSO [36], artificial immune system (AIS) [36], Vaccine-AIS [36], harmony search algorithm (HSA) [40], ant colony algorithm (ACA) [41] and evolutionary particle swarm optimization (EPSO) [42] have been used to solve the aforementioned problems. Bayat *et al.* [34] propose a new heuristic method base on UVDA for simultaneously optimizing reconfiguration with DG siting and sizing with the aim of minimizing losses. Chidanandappa *et al.* [35] implements an algorithm which predicts optimum reconfiguration plan for power distribution system with multiple PV generators. Genetic algorithm is used to solve the resulting problem and forward backward load flow method is implemented to consider time varying load conditions. Jangir *et al.* [38] propose a methodology for determining optimal placement and sizing of DG units to minimize the cost of annual energy losses, and also to enhance node voltage profiles of the system. The optimal DG allocation problem is solved using MPSO algorithm whose control parameters are varied with iteration in order to improve its performance. Guan et al. [39] presents a methodology for DSR considering different types of DGs with an overall objective of minimizing real power losses. DQPSO has been applied to solve feeder reconfiguration with DGs. Rao *et al.* [40] proposes a new methodology to solve the network reconfiguration problem in the presence of distributed generation (DG) with an objective of minimizing real power losses and improving voltage profile in distribution systems. A metaheuristic HSA is used to simultaneously reconfigure and identify the optimal locations for installing DG units in a distribution network system. Sensitivity analysis is used to identify the optimal locations of DG units. Different scenarios of DG placement and network reconfiguration are considered to study the performance of the proposed method. Sulaima et al. [42] proposes EPSO, a hybrid solution method obtained by combining PSO and EP solution methods. The proposed method finds the optimal network reconfiguration and optimal size of DG simultaneously. Esmaeilian and Fadaeinedjad [43] present a novel hybrid method of metaheuristic and heuristic algorithms to solve distribution network reconfiguration in the presence of DGs, especially considering solar PV type DGs. The solution method, according to the authors, is capable of boosting robustness and reducing the computational time. Maciel *et al.* [44] report a broad comparison of different meta-heuristics solution techniques applied on multi objective problems.

Abu-Mouti and El-Hawary [45] propose a new population-based Artificial Bee Colony (ABC) for solving a mixed-integer non-linear optimization problem for DG planning. Elmitwally *et al.* [46] have developed a multi-agent control system (MACS) for solving the aforementioned problem. An hybrid solution method is proposed in [43].In [47], authors make a multi-agent architecture. Scenario analysis (SA) and concepts of receding horizon control (RHC) are employed in [48]. An approach for optimal short-term operational scheduling with intermittent RES in an active distribution system is proposed in [49].

2.4 - Energy storage system and Distributed Generation

2.4.1 - A General Overview

Energy storage system (ESS) is one of the most important components in an integrated system because it helps to counteract the unpredictable variation of the energy supplied by intermittent renewable energy sources such as wind and solar. High penetration of RESs increases the variability and the uncertainty of the power supply, negatively affecting the optimal operation of traditional power systems and network reliability. ESS levels the mismatch between power generation and demand, making it an important component for economic and technical reasons [24], [50].

On the other hand, deregulated electricity markets principally introduce a competitive environment for power producers, resulting in high capital cost requirement for meeting peak demands and volatile electricity prices. ESS is considered as one of the solutions for stabilizing the supply of energy to avert wasteful power production and high prices in peak times. IEA predicts a significant growth in the share of variable RES in total electricity generation, from 6.9% in 2011 to 23.1% by 2035 within the EU [50]. The European Commission has recognized electricity storage as one of the strategic energy technologies to accomplish the EU's energy targets by 2020 and 2050. The US Department of Energy (DOE) has also identified energy storage as a solution for grid stability [50]. Storage technologies can be basically classified on storage duration (lifetime) or form of storage. Based on the storage duration, ESS can be classified as short-, medium- and long-term storage systems, and from the storage medium viewpoint, ESSs can be classified as mechanical, chemical and electrical energy storage systems. Each ESS type has different technical and economic characteristics, and applications [24], [51].

Some of the main reasons of integrating ESSs in distribution network systems can been seen in the graphical illustration, shown in Figure 2.2. These include:

1) Meeting demand and reliability in grid's peak hours: Demand involves hourly, daily, weekly and seasonal variations. Traditionally, in power systems, the production capacity is often maintained huge enough to meet the peak demands that occur just a few hours per year. This results in oversized, inefficient, environmentally unfriendly and uneconomical power systems. In this regard, ESSs becomes a good alternative to store power during hours of low demand to be used later in peak demand hours, deferring the construction of larger power capacity.

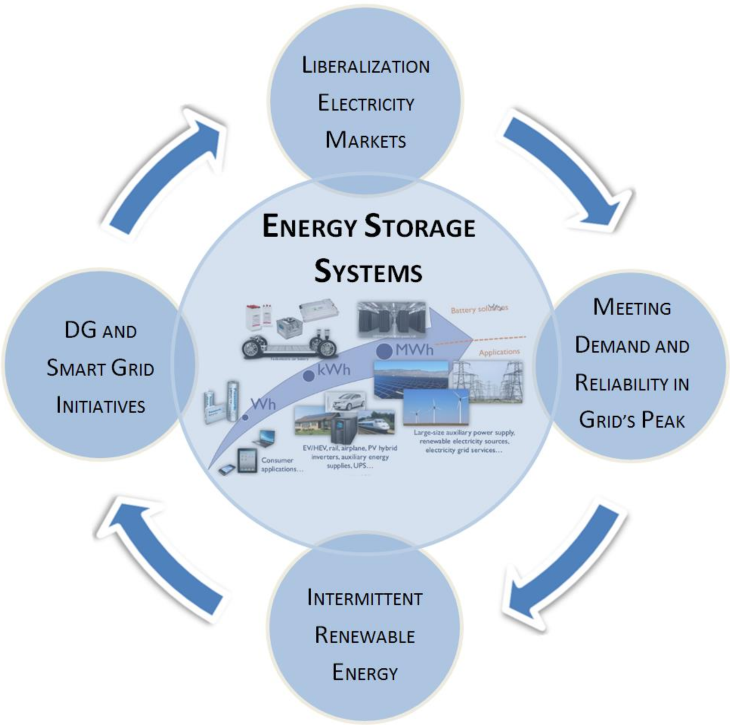

Figure 2.2 - The main reasons to adopt Energy Storage Systems in network (adapted from [52]).

2) Liberalized electricity markets: Another potential use of ESS is the substantial profits that can be garnered from price arbitrage, due to changing electricity from low demand periods to the peak ones. The lucrativeness of ESS in price arbitrage depends on the level of fluctuations in spot prices. The use of ESS in balancing markets and other deregulated ancillary services may stack the benefits, resulting in more economic appeal. Adopting an optimal strategy in charge/discharge scheduling and more improvements in price forecasting are the two important parameters in increasing the incomes from ESS in price arbitrage.

3) Intermittent renewable energy: Energy policies promote the use of RES to reduce carbon emissions. Intermittency of RES, like wind or solar, bring new challenges to the optimal operation of power systems such as frequency fluctuations and voltage flicker. ESS can enhance the use of RES. For instance, it can store extra uncontrollable RES power generation during periods of high RES production and low demand so that the stored energy can be used at a desirable time (often during peak demand hours). ESS can contribute in relieving the fluctuation suppression, low voltage rides through, and voltage control support, resulting in smooth power output.

4) DG and smart grid initiatives: ESS can contribute as an uninterruptible power supply (UPS) and overcoming voltage drops in decentralized and inflexible power systems. The integration of ESS is especially critical in remote islands and microgrids with more RES integration [50]–[52]. In such systems, ESSs result in higher energy security and lower emissions.

As mentioned in the previous chapter, RES based power production is partially unpredictable and independent of human action. Furthermore, the moments of high RES generation may not coincide with the moments of the peak demand. There are two technologies that can help to resolve this problem:

First, ESS and Hybrid Distributed Generation Systems. Energy storage has an important contribution to the strategic value of the future of electric network. With increasing level of RES and demand, ESSs will become very important for the operation of the system as a whole, because this will increase the reliability and stability and flexibility of the system. Energy stored during low demand periods will cover demand during peak periods. The use of power reserves when the energy is most needed and more expensive helps to overcome the problem of unpredictability and variable power production from RES. Second, ESS helps to reduce congestion in transmission and distribution systems and to supply energy during outages.

One of the major issues with energy storage is the associated high capital cost. Apart from pumped hydro, other storage technologies are undergoing continuous improvements both in terms of performance as well as cost [23], [24]. The costs of most ESS technologies are expected to dramatically fall in the years to come, and their economic viabilities are increasing from time to time.

Optimal performance of power distribution networks is significantly influenced by network configuration, location and size of DG units and ESSs. The presence of ESSs in distribution systems leads to some loads to be supplied in faulty conditions [53].

2.4.2 – Simultaneous Integration of DGs and ESSs – A Literature Review

As it has been stated earlier, the placement and sizing optimization of ESS is important to mitigate the unpredictable variation of the energy supplied by RES. In [54], Chauhan and Saini present a detailed review on this subject area, including the individual ESS applications with respect to several storage options, settings, sizing methodologies and control. Like in the previous sections, based on the solution techniques applied to solve the problem pertaining to the simultaneous planning of DGs and ESSs, the literature can be categorized as: 1) heuristic and metaheuristic techniques; 2) mathematical techniques; 3) hybrid techniques.

A set of heuristic and metaheuristic techniques are employed in the literature. Saboori *et al.* [51] uses PSO to find the optimal location and size of ESSs with the intention of reliability improvement in radial electrical distribution networks. The proposed optimal ESSs planning is addressed as a minimization problem which aims at minimizing the cost of energy not supplied (ENS) as well as installation costs of ESSs costs at the same time while respecting a number of technical constraints. These include security constraints such as voltage and line flows limits. Fossati *et al.* [55] propose a method to find the energy and power capacities of the storage system that minimizes the operating cost of a microgrid. The energy management strategy used is based on a fuzzy expert system which is responsible for setting the power output of the ESS. The design of the energy management strategy is carried out by means of a genetic algorithm that is used to set the fuzzy rules and membership functions of the expert system. Given that the size of the storage system has a major influence on the energy management strategy (EMS), the EMS and ESS capacities are jointly optimized. In addition, the proposed method uses an aging model to predict the lifetime of the ESS. Chen *et al.* [56] present a methodology for the optimal allocation and economic analysis of ESS in microgrids on the basis of net present value (NPV).

As the performance of a microgrid strongly depends on the allocation and arrangement of its ESS, optimal allocation methods and economic operation strategies of the ESS devices are required for the microgrid. A matrix real-coded genetic algorithm is applied to find optimal NPV, in which each GA chromosome consists of a 2-D real number matrix representing the generation schedule of ESS and distributed generation sources. Hu *et al.* [57] propose a bi-level-programming-based model to take the interaction of allocation and operation into consideration at the same time, with the external level optimizing allocation and the internal level optimizing operation. A genetic numerical algorithm is proposed to solve the bi-level model.

The literature also includes some works that use mathematical techniques. Levron *et al.* [58] suggest dynamic programing to compute the optimal energy management of storage devices in grid-connected microgrids. Stored energy is controlled to balance the power of loads and renewable sources, over the time domain, minimizing the overall cost of energy. The algorithm incorporates an arbitrary network topology, which can be a general one-phase, balanced, or unbalanced three-phase system. It employs a power flow solver in network domain, within a dynamic programming recursive search in time domain. Mohamed Abd el Motaleb *et al.* [59] performs optimal sizing for a hybrid power system with wind/energy storage sources based on stochastic modeling of historical wind speed and load demand. The sequential Monte Carlo simulation is performed to chronologically sample the system states. An objective function based on self-adapted evolutionary strategy is proposed to minimize the one-time investment and annual operational costs of the wind/energy storage sources and the effect of the cycle efficiency and charging/discharging rate of different energy storage units on the system cost is investigated. Crespo Del Granado *et al.* [60] have modeled the impact of real-time pricing schemes (from the smart grids perspective) on a hybrid DG system (mixed generation for heating and electricity loads) coupled with storage units. They have formulated a dynamic optimization model to represent a real-life urban community's energy system composed of a co-generation unit, gas boilers, electrical heaters and a wind turbine. Farrokhifar [61] calculates electricity grid losses while considering limitations of using energy storage devices. Dynamic programming is used to solve the problem on CIGRÉ low voltage grid as a standard benchmark. Srivastava *et al.* [62] analyze the technical and economic impacts of distributed generators along with energy storage devices on distribution systems. The technical analysis includes analyzing the transient stability of a system with DGs and energy storage devices, such as a battery and ultracapacitor. The DGs are represented by small synchronous and induction generators. Different types and locations of faults and different penetration levels of DGs are considered in the analysis. For economic analysis, the costs of the system with different DG technologies and energy storage devices are compared using the software tool "hybrid optimization model for electric renewables (HOMER)." Atwa and El-Saadany [63] propose a methodology for allocating an ESS in a distribution system with a high penetration of wind energy. The ultimate goal is to maximize the benefits for both the DG owner and the utility by sizing the ESS to accommodate all amounts of spilled wind energy and by then releasing the stored energy to the system when needed so that the annual cost of the electricity is minimized. In addition, a cost/benefit analysis has been conducted in order to verify the feasibility of installing an ESS from the perspective of both the utility and the DG owner. These data are incorporated into two separate OPF formulations in order to determine the annual cost of spilled energy and the optimum allocation of the ESS in the distribution system.

Hybrid methods in literature are also proposed. Arefifar and Mohamed [64] propose two different strategies for constructing reliable microgrids considering temporary and sustained faults, and supply-adequate microgrids considering both real and reactive power self-sufficiency, defined as a new probabilistic index for simultaneous consideration of reliability indices and real and reactive supply-adequacy for the construction of microgrids. All this take into account the uncertainty in the characteristics of the DG units and loads for constructing and enhancing the microgrids. For the sensitivity studies, proposed two corrective actions are proposed to improve the performance of microgrids in terms of reliability and supply-adequacy. Three different types of algorithms are used at different stages, including TS optimization algorithm as the main optimization method and graph theory-related algorithms as well as forward–backward-based probabilistic power flow methods.

2.5 – Distributed System Reconfiguration, Distributed Generation and Energy Storage Systems

2.5.1 - Motives of Joint Optimization of DSR, DG and ESS Placement

A DSR along with optimal size and location of DG and ESS considers the aggregate potential of each one on the system.

The ultimate goal for the simultaneous consideration of DSR and ESS and DG deployment is to help the integration of large-scale RES. Figure 2.3 illustrates the integration of various technologies in the distribution system. The increased penetration of variable renewable DGs will have positive and negative impact on system conditions. Conventional electrical networks carry a unidirectional power flow. The introduction of DGs implies a bidirectional power flow. DSR increases to possibility of achieving some operational aims. Variability of RES will be counterbalanced by ESS. In other words, ESS integrated in the network system will counteract the unpredictable variation of the energy supplied by intermittent RES. In addition, ESS will balance the demand and power generation. Storage of energy will occur during period’s high RES power production and low demand, and is released during periods of peak demand.

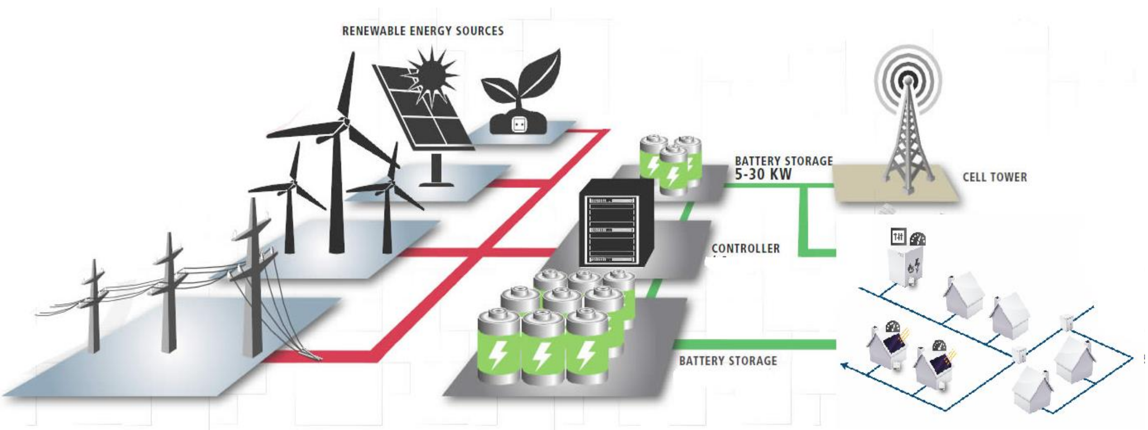

Figure 2.3 - Integration of various technologies in the distribution system- illustrative figure (Figure adapted from [65] and [66].

2.5.2 - Joint Optimization of DSR, DG and ESS Placement - A Literature Review

Hosseini and Abbasi [53] propose, at first, an approach for ENS calculation in the presence of DGs and storage systems. Then, the DSR problem along with the optimal DG allocation and sizing problems solved by the Non-dominated Sorting Genetic Algorithm II (NSGA-II). This solution approach allows the losses, ENS and costs of each topology to be separately optimized under specific loads and constraints. Quevedo et al. [65] presents a two-stage stochastic linear programming model to solve the optimization problem and find the best combination of generation, demand and electrical energy storage under islanding conditions. The mathematical formulation of this work consists of a two-stage MILP reconfiguration model considering wind power and energy storage in Electrical Distribution Systems (EDS). Hence, an Alternative Current (AC) power flow is approximated through linear expressions to linearize the model. In [65], a two-stage stochastic MILP reconfiguration model considering wind energy and ESS has been implemented in order to maximize load and generation under islanding conditions. The objective function of the optimization model is based on real power with additional constraints for reactive power in the islanded area. Novoselnik and Baotic [66] present a nonlinear model for a predictive control strategy of a dynamic reconfiguration of electrical power distribution systems with distributed generation and storage. The goal of the proposed control strategy is to find the optimal radial network topology and the optimal power references for the controllable generators and energy storage units that will minimize cumulative active power losses while satisfying operational constraints. By utilizing recent results on convex relaxation of the power flow constraints, the proposed dynamic reconfiguration algorithm can be formulated as a MISOCP. Furthermore, if polyhedral approximations of second order cones are used then the underlying optimization problem can be solved as a MILP. Quevedo et al. [22] propose an optimal contingency assessment model using a two-stage stochastic linear programming including wind power generation and a generic ESS. The optimization model is applied to find the best radial topology by determining the best switching sequence considering contingencies

2.6 - Summary

This chapter has presented a detailed review of relevant works in the subject areas of distribution network reconfiguration, deployment of distributed generation and energy storage systems from the perspective of maximizing DG integration. In addition, the most relevant works in the literature have been classified based on typically used solution methodologies. The organization of this review is characterized by the evolution of approaches, from the simplest to the most complex with regard to the integration of technology in the network.

It has been found out that the variety of methods and objectives applied on the reviewed works, lack detailed information about tests and results (computation times, hardware, development interface, etc.), especially earlier works, making it hard to compare different methodologies. On this perspective, a multi-objective approach, as in this thesis, has been increasingly gaining attention because it makes a weighted representation of the various costs of real problems, a more orthodox approach.

Remain patent the global consensus for the integration of DG sources, specially RES as a way to meet the growing demand for electric energy and to reduce the carbon footprint of energy production. Nevertheless, the realization of this considerable objective faces two big challenges. The first is the variability and uncertainty introduced on the system by RES and the second is the stability and quality of energy. To overcome these challenges, it is necessary to integrate a set of enabling technologies, as well as design an effective coordination mechanism among different technologies in distribution systems. It should be noted that, in addition to these challenges, there exists a set of system restrictions related to operation as well as economics that cannot be violated.

The integration of these technologies is a topic which has being studied for some time, yet, integration of a specific set, namely DSR, DG and ESS has not been adequately studied. The contribution of the present work therefore lies in the joint analysis of these technologies with the specific aims of improving system flexibility, increasing RES penetration, reducing losses, enhancing system stability and reliability.

Chapter 3

Problem Formulation - A Mixed Integer Linear Programming Approach

This chapter presents a complete description of the mathematical optimization model developed to study the impacts of network switching and/or reinforcement as well as installing DESSs on the level of renewable power integrated in the system. The proposed planning tool is a dynamic and multi-objective stochastic mixed integer linear programming (S-MILP) model, which jointly takes into account the optimal RES-based DGs and DESS integration in coordination with distribution network reinforcement and/or switching.

3.1 - Algebraic Formulation of the Joint Planning Problem

The dynamic and multi-objective S-MILP optimization model developed in this thesis is described as follows.

3.1.1 -Objective Function

The problem is formulated as a multi-objective stochastic MILP with an objective of overall cost minimization as in (3.1). The objective function in (3.1) is composed of Net Present Value (NPV) of five cost terms each weighted by a certain relevance factor $\gamma_j; \forall j \in \{1,2,\ldots,5\}$.

The first term in (3.1), $TInvC$, represents the total investment costs under the assumption of perpetual planning horizon. In other words, "the investment cost is amortized in annual instalments throughout the lifetime of the installed component".

Here, the total investment cost is the sum of investment costs of DGs, distribution network system (DNS) components (feeders and transformers) and ESSs, as in (3.2). And, this cost is computed as in (3.7)-(3.9).

The second term, TMC, in (3.1) denotes the total maintenance costs which is given by the sum of maintenance costs of new and existing DGs as well as that of DNS components and ESSs at each stage and the corresponding costs incurred after the last planning stage, as in (3.3). Note that the latter depend on the maintenance costs of the last planning stage according a perpetual planning horizon. These maintenance costs are computed according to Eqs. (3.10)-(3.12).

The third term TEC in (3.1) refers to the total cost of energy in the system, which is the sum of the cost of power produced by new and existing DGs, supplied by ESSs and purchased from upstream at each stage as in (3.4). Equation (3.4) also includes the total energy costs incurred after the last planning stage under the assumption of perpetual planning horizon. These depend on the energy costs of the last planning stage. The detailed mathematical expressions for computing the cost of DG power produced and ESS power supplied as well as that of purchased power are given in (3.13), (3.14) and (3.15), respectively. The fourth term $TENSC$ represents the total cost of unserved power in the system, given as in (3.5). And, this is computed using Eq. (3.16). The last term $TEmiC$ gathers the total emission costs in the system, given by the sum of emission costs for the existing and new DGs (3.17)-(3.19) as well that of purchased power (3.20).

$$Minimize\ TC = \gamma_1 * TInvC + \gamma_2 * TMC + \gamma_3 * TEC + \gamma_4 * TENSC + \gamma_5 * TEmiC \tag{3.1}$$

As mentioned earlier, the objective function is composed of five terms which are associated with the relevance factors. These factors can have a single purpose or dual purposes. The first one is to give the flexibility for the planner to include/exclude each cost term from the objective function. In this case, the associated relevance factor is set to 1 if the cost term is included; 0, otherwise. Another purpose of these factors boils down to the relative weight in which the planner wants to give to each cost term. To emphasize the importance of a given cost term, a relatively higher value can be assigned than any other term in the objective function.

$$TInvC = \underbrace{\sum_{t \epsilon \Omega^t} (1+r)^{-t} (InvC_t^{DG} + InvC_t^{DNS} + InvC_t^{ES})/r}_{NPV\ of\ investment\ cost} \tag{3.2}$$

$$TMC = \underbrace{\sum_{t \epsilon \Omega^t} (1+r)^{-t}\ (MntC_t^{DG} + MntC_t^{DNS} + MntC_t^{ES})}_{NPV\ of\ maintenance\ costs} + \underbrace{(1+r)^{-T} (MntC_T^{DG} + MntC_T^{DNS} + MntC_T^{ES})/r}_{NPV\ maintenance\ costs\ incured\ after\ stage\ T} \tag{3.3}$$

$$TEC = \underbrace{\sum_{t \epsilon \Omega^t} (1+r)^{-t}\ (EC_t^{DG} + EC_t^{SS} + EC_t^{ES})}_{NPV\ of\ operation\ costs} + \underbrace{(1+r)^{-T} (EC_T^{DG} + EC_T^{SS} + EC_T^{ES})/r}_{NPV\ operation\ costs\ incured\ after\ stage\ T} \tag{3.4}$$

$$TENSC = \underbrace{\sum_{t\epsilon\Omega^t}(1+r)^{-t}\ ENSC_t}_{NPV\ of\ \ reliability\ costs} + \underbrace{(1+r)^{-T}ENSC_T/r}_{NPV\ reliability\ costs\ incured\ after\ stage\ T} \tag{3.5}$$

$$TEmiC = \underbrace{\sum_{t\epsilon\Omega^t}(1+r)^{-t}\ (EmiC_t^{DG} + EmiC_t^{SS})}_{NPV\ emission\ costs} + \underbrace{(1+r)^{-T}(EmiC_T^{DG} + EmiC_T^{SS})/r}_{NPV\ emission\ costs\ incured\ after\ stage\ T} \tag{3.6}$$

Equation (3.2) translates the total investment costs under the planning horizon, where $InvC_t^{DG}$ denotes the investment costs of DG's, $InvC_t^{DNS}$ is the investment costs in the distribution network system and $InvC_t^{ES}$ is the investment cost in ESS. Equation (3.3) represents the total maintenance costs of new and existing DG's, of DNS components and ESSs at each stage and these costs are updated by the NPV factor associated to each year. $MntC_t^{DG}$ are the maintenance costs of DG, $MntC_t^{DNS}$ the maintenance costs of distribution network system and $MntC_t^{ES}$ maintenance costs of ESSs. Equation (3.4) shows the total cost of energy in the system, which is the sum of the cost of power produced by new and existing DGs, supplied by ESSs and purchased from upstream at each stage. This function is due to the NPV operation costs and NPV operation costs updated each year of the planning horizon. $TENSC$ in (3.5) represents the total cost of unserved power in the system. This is interpreted as the energy not supplied costs ($ENSC$) and $ENSC$ updated costs at each year of planning horizon. The total emission costs of power production using DG ($EmiC_t^{DG}$) and the emission cost of purchased power ($EmiC_t^{SS}$)is presented in (3.6). This function also relates the updated costs at each year of the planning horizon.

Equations (3.7)—(3.9) represent the investment costs of DGs, feeders and energy storage system, respectively. Notice that all investment costs are weighted by the capital recovery factor, $\frac{r(1+r)^{LT}}{(1+r)^{LT}-1}$. The formulations in (3.7)—(3.10) ensure that the investment cost of each component added to the system is considered only once in the summation.

$$InvC_t^{DG} = \sum_{g\epsilon\Omega^g}\sum_{i\epsilon\Omega^i}\frac{r(1+r)^{LT_g}}{(1+r)^{LT_g}-1}IC_{g,i}(x_{g,i,t} - x_{g,i,t-1})\ ;where\ x_{g,i,0} = 0 \tag{3.7}$$

$$\begin{aligned} InvC_t^{DNS} = & \sum_{k\epsilon\Omega^\ell}\frac{r(1+r)^{LT_k}}{(1+r)^{LT_k}-1}IC_k(x_{k,t} - x_{k,t-1}) \\ & + \sum_{ss\epsilon\Omega^{ss}}\sum_{tr\epsilon\Omega^{tr}}\frac{i(1+i)^{LT_{tr}}}{(1+i)^{LT_{tr}}-1}IC_{tr}\left(x_{tr,ss,t} - x_{tr,ss,t-1}\right); \end{aligned} \tag{3.8}$$

$$InvC_t^{ES} = \sum_{c\epsilon\Omega^c}\sum_{i\epsilon\Omega^i}\frac{r(1+r)^{LT_{ess}}}{(1+r)^{LT_{es}}-1}IC_c(x_{es,i,t} - x_{es,i,t-1})\ ;where\ x_{es,i,0} = 0 \tag{3.9}$$

In (3.7), $IC_{g,i}$ represents the investment cost of DG, $x_{g,i,t}$ is the investment variables for DG. $\mathrm{LT_g}$ is the life time of DG. Equations (3.9) and (3.10) are also based on the same principle. In (3.8), LT_k and LT_{tr} are the lifetime of distribution lines and transformers, respectively. And, in (3.9), IC_k and IC_{tr} are the investment costs on distribution lines and transformers, respectively.

Equation (3.10) stands for the maintenance costs of new MC_g^N and existing DGs MC_g^Eat each time stage. The maintenance cost of a new/existing feeder is included only when its corresponding investment/utilization variable is different from zero in (3.11). Equation (3.12) is related to the maintenance costs at each stage of energy storage.

$$MntC_t^{DG} = \sum_{g\epsilon\Omega^g}\sum_{i\epsilon\Omega^i} MC_g^N\, x_{g,i,t} + \sum_{g\epsilon\Omega^g}\sum_{i\epsilon\Omega^i} MC_g^E\, u_{g,i,t} \tag{3.10}$$

$$MntC_t^{DNS} = \textstyle\sum_{k\epsilon\Omega^{e\ell}} MC_k^E\, u_{k,t} + \sum_{k\epsilon\Omega^{n\ell}} MC_k^N x_{k,t} + \displaystyle\sum_{tr\epsilon\Omega^{E\_tr}} MC_{tr}^E\, u_{tr,ss,t} + \sum_{tr\epsilon\Omega^{N\_tr}} MC_k^N x_{tr,ss,t} \tag{3.11}$$

$$MntC_t^{ES} = \sum_{c\epsilon\Omega^c}\sum_{i\epsilon\Omega^i} MC_{es} x_{es,i,t} \tag{3.12}$$

The total cost of power produced by new and existing DGs is given by equation (3.13). Note that these costs depend on the amount of power generated at each scenario, snapshot and stage. Therefore, these costs represent the expected costs of operation. Similarly, equations (3.14) and (3.15) respectively account for the expected costs of energy supplied by the energy storage system, and that purchased from upstream (i.e. transmission grid).

$$EC_t^{DG} = \sum_{s\epsilon\Omega^s} \rho_s \sum_{w\epsilon\Omega^w} \pi_w \sum_{g\epsilon\Omega^g}\sum_{i\epsilon\Omega^i} (OC_{g,i,s,w,t}^N P_{g,i,s,w,t}^N + OC_{g,i,s,w,t}^E\, P_{g,i,s,w,t}^E) \tag{3.13}$$

$$EC_t^{ES} = \sum_{s\epsilon\Omega^s} \rho_s \sum_{w\epsilon\Omega^w} \pi_w \sum_{es\in\Omega^{es}} \lambda_{s,w,t}^{es} P_{es,i,s,w,t}^{dch} \tag{3.14}$$

$$EC_t^{SS} = \sum_{s\epsilon\Omega^s} \rho_s \sum_{w\epsilon\Omega^w} \pi_w \sum_{\varsigma\epsilon\Omega^\varsigma} \lambda_{s,w,t}^{\varsigma} P_{\varsigma,s,w,t}^{SS} \tag{3.15}$$

The penalty for the unserved power, given by (3.16), is also dependent on the scenarios, snapshots and time stages. Equation (3.16) therefore gives the expected cost of unserved energy in the system.

$$ENSC_t = \sum_{s \epsilon \Omega^s} \rho_s \sum_{w \epsilon \Omega^w} \sum_{i \epsilon \Omega^i} \pi_w \upsilon_{s,w,t} \delta_{i,s,w,t} \tag{3.16}$$

The expected emission costs of power generated by new and existing DGs are given by (3.17)-(3.19), and that of energy purchased from the grid is calculated using (3.20). Note that, for the sake of simplicity, a linear emission cost function is assumed here. In reality, the emission cost function is highly nonlinear and nonconvex, as in [44].

$$EmiC_t^{DG} = EmiC_t^N + EmiC_t^E \tag{3.17}$$

$$EmiC_t^N = \sum_{s \epsilon \Omega^s} \rho_s \sum_{w \epsilon \Omega^w} \pi_w \sum_{g \epsilon \Omega^g} \sum_{i \epsilon \Omega^i} \lambda_{s,w,t}^{CO_2 e} ER_g^N P_{g,i,s,w,t}^N \tag{3.18}$$

$$EmiC_t^E = \sum_{s \epsilon \Omega^s} \rho_s \sum_{w \epsilon \Omega^w} \pi_w \sum_{g \epsilon \Omega^g} \sum_{i \epsilon \Omega^i} \lambda_{s,w,t}^{CO_2 e} ER_g^E P_{g,i,s,w,t}^E \tag{3.19}$$

$$EmiC_t^{SS} = \sum_{s \epsilon \Omega^s} \rho_s \sum_{w \epsilon \Omega^w} \pi_w \sum_{\varsigma \epsilon \Omega^\varsigma} \sum_{i \epsilon \Omega^i} \lambda_{s,w,t}^{CO_2 e} ER_\varsigma^{SS} P_{\varsigma,s,w,t}^{SS} \tag{3.20}$$

3.1.2 -Constraints

a) Kirchhoff's current law (Active power balance)

The active power balance at each node is enforced by equation (3.21):

$$\begin{aligned} &\sum_{g \epsilon \Omega^{DG}} \left(P_{g,i,s,w,t}^E + P_{g,i,s,w,t}^N\right) + \sum_{es \epsilon \Omega^{es}} \left(P_{es,i,s,w,t}^{dch} - P_{es,i,s,w,t}^{ch}\right) + P_{\varsigma,s,w,t}^{SS} + \sum_{in,k \epsilon i} P_{k,s,w,t} - \sum_{out,k \epsilon i} P_{k,s,w,t} + \delta_{i,s,w,t} \\ &= \sum_{in,k \epsilon i} 0.5 \varphi_{k,s,w,t} + \sum_{out,k \epsilon i} 0.5 \varphi_{k,s,w,t} + D_{s,w,t}^i \; ; \; \forall \varsigma, \forall \varsigma \epsilon i \end{aligned} \tag{3.21}$$

Equation (3.21) denotes that the sum of all incoming flows should be equal to the sum of all outgoing flows at each node. The losses in every feeder are considered as "virtual loads" which are equally distributed between the nodes connecting the feeder Note that losses are a quadratic function of flows (not shown here). Hence, they are linearized using first order approximation, as in [68].

b) Energy Storage Model Constraints

For the sake of simplicity, a generic ESS is employed here. This is modeled by the set of constraints in (3.22)-(3.28). Equations (3.22) and (3.23) represent the bounds of power capacity of the ESS while being charged and discharged, respectively. Inequality (3.24) prevents simultaneous charging and discharging operation of ESS at the same operational time w. The amount of stored energy within the ESS reservoir at a given operational time w as a function of the energy stored until $w-1$ is given by (3.25). The maximum and minimum levels of storages in the operational time w are also considered through inequality (3.26). Equation (3.27) shows the initial level of stored energy in the ESS as a function of its maximum reservoir capacity. In a multi-stage planning approach, Equation (3.28) ensures that the initial level of energy in the ESS at a given year is equal to the final level of energy in the ESS in the preceding year. Here, η_{es}^{dch} is assumed to be $1/\eta_{es}^{ch}$.

$$0 \leq P_{es,i,s,w,t}^{ch} \leq I_{es,i,s,w,t}^{ch} x_{es,i,t} P_{es,i}^{ch,max} \tag{3.22}$$

$$0 \leq P_{es,i,s,w,t}^{dch} \leq I_{es,i,s,w,t}^{ch} x_{es,i,t} P_{es,i}^{ch,max} \tag{3.23}$$

$$I_{es,i,s,w,t}^{ch} + I_{es,i,s,w,t}^{dch} \leq 1 \tag{3.24}$$

$$E_{es,i,s,w,t} = E_{es,i,s,w-1,t} + \eta_{ch,es} P_{es,i,s,w,t}^{ch} - \eta_{dch,es} P_{es,i,s,w,t}^{dch} \tag{3.25}$$

$$E_{es,i}^{min} x_{es,i,t} \leq E_{es,i,s,w,t} \leq x_{es,i,t} E_{es,i}^{max} \tag{3.26}$$

$$E_{es,i,s,w_0,T1} = \mu_{es} x_{es,i,T1} E_{es,i}^{max} \tag{3.27}$$

$$E_{es,i,s,w_1,t+1} = E_{es,i,s,W,t} \tag{3.28}$$

Inequalities (3.22) and (3.23) involve products of charging/discharging indicator variables and investment variable. In order to linearize this, new continuous positive variables $z_{es,i,s,w,t}^{ch}$, and $z_{es,i,s,w,t}^{dch}$, which replaces the bilinear products in each constraint, is introduced such that the set of linear constraints in (3.29) and (3.30) hold. For instance, the product $I_{es,i,s,w,t}^{dch} x_{es,i,t}$ is replaced by the positive variable $z_{es,i,s,w,t}^{dch}$. Then, the bilinear product is decoupled by introducing the set of constraints in (3.29) [69]. Similarly, the product $I_{es,i,s,w,t}^{ch} x_{es,i,t}$is decoupled by including the set of constraints (3.30).

$$z_{es,i,s,w,t}^{dch} \leq x_{es}^{max} I_{es,i,s,w,t}^{dch} \; ; \; z_{es,i,s,w,t}^{dch} \leq x_{es,i,t} \; ; z_{es,i,s,w,t}^{dch} \geq x_{es,i,t} - \left(1 - I_{es,i,s,w,t}^{dch}\right) x_{es}^{max} \tag{3.29}$$

$$z_{es,i,s,w,t}^{ch} \leq x_{es}^{max} I_{es,i,s,w,t}^{ch} \; ; \; z_{es,i,s,w,t}^{ch} \leq x_{es,i,t} \; ; z_{es,i,s,w,t}^{ch} \geq x_{es,i,t} - \left(1 - I_{es,i,s,w,t}^{ch}\right) x_{es}^{max} \tag{3.30}$$

a) Active Power Limits of DGs

The active power limits of existing generators are given by (3.31). In the case of new generators, the corresponding constraints are (3.32). Note that the binary variables multiply both bounds to make sure that the power generation variable is zero when the generator remains either unutilized or unselected for investment.

$$P_{g,i,s,w,t}^{E,min} u_{g,i,t} \leq P_{g,i,s,w,t}^{E} \leq P_{g,i,s,w,t}^{E,max} u_{g,i,t} \tag{3.31}$$

$$P_{g,i,s,w,t}^{N,min} x_{g,i,t} \leq P_{g,i,s,w,t}^{N} \leq P_{g,i,s,w,t}^{N,max} x_{g,i,t} \tag{3.32}$$

It should be noted that these constraints are applicable only for conventional DGs. In the case of variable generation source (such as wind and solar PV), the upper bound $P_{g,i,s,w,t}^{max}$ should be set equal to the minimum of the actual production level at a given hour, which is dependent on the level of primary energy source (wind speed and solar radiation), and the rated (installed) capacity of the generating unit. And, the lower bound $P_{g,i,s,w,t}^{max}$ in this case is simply set to zero.

b) Active Power Limits of Power Purchased

$$P_{s,w,t}^{SS,min} \leq P_{s,w,t}^{SS} \leq P_{s,w,t}^{SS,max} \tag{3.33}$$

For technical reasons, the power that can be purchased from the transmission grid could have minimum and maximum limits, which is enforced by (3.33). However, it is understood that setting the maximum and minimum limits is difficult. These constraints are included here for the sake of completeness. In this work, these limits are set to 1.5 times the minimum and maximum levels of total load in the system.

c) Logical constraints

The set of logical constraints in (3.34) ensure that an investment decision cannot be reversed. In addition to the constraints described above, the direct current (DC) based network model and radiality related constraints presented in [68] are used here.

$$x_{k,t} \geq x_{k,t-1}; \;\; x_{g,i,t} \geq x_{g,i,t-1}; \;\; x_{es,i,t} \geq x_{es,i,t-1} \tag{3.34}$$

d) Radiality constraints

There are two conditions that must be fulfilled in order a distribution network system (DNS) to be radial. First, the solution must have $N_i - N_{SS}$ circuits. Second, the final topology should be connected. Equation (3.35) represents the first necessary condition for maintaining the radial topology of DNs.

$$\sum_{k \in \Omega^{ij}} OR(x_{k,t}, u_{k,t}) = N_i - N_{SS} \quad ; \forall t \tag{3.35}$$

Note that the above equation assumes line investment is possible in all corridors. Hence, in a given corridor, we can have either an existing branch or a new one, or both connected in parallel, depending on the economic benefits of the final setup (solution) brings about to the system. The radiality constraint in (3.35) then has to accommodate this condition. One way to do this is using the Boolean logic operation, as in (3.35). Unfortunately, this introduces nonlinearity. We show how this logic can be linearized using an additional auxiliary variable $z_{k,t}$ and the binary variables associated to existing and new branches i.e. $u_{k,t}$ and $x_{k,t}$, respectively. Given$z_{k,t} := OR(x_{k,t}\ ,\ u_{k,t})$,this Boolean operation can be expressed using the following set of linear constraints:

$$z_{k,t} \leq x_{k,t} + u_{k,t}; \; z_{k,t} \geq x_{k,t}; \; z_{k,t} \geq u_{k,t}; 0 \leq z_{k,t} \leq 1 \quad ; \forall t \tag{3.36}$$

Then, the radiality constraints in (69) can be reformulated using the $z_{k,t}$ variables as:

$$\sum_{k \in \Omega^{ij}} z_{k,t} = N_i - N_{SS} \qquad ; \forall t \tag{3.37}$$

When all loads in the DNS are only fed by power from substations, the final solution obtained automatically satisfies the two aforementioned conditions; hence, no additional constraints are required i.e. (3.36) along with (3.37) are sufficient to guarantee radiality. However, it should be noted that in the presence of DGs and reactive power sources, these constraints alone may not ensure the radiality of the distribution network, as pointed out in [70] and further discussed in [71].

3.2 – Summary

This chapter has presented a full description of the proposed dynamic and multi-objective S-MILP model, which jointly takes into account the optimal RES-based DGs and DESS integration in coordination with distribution network reinforcement and/or switching.

The problem has been formulated as with an objective of overall cost minimization. The objective function is composed of Net Present Value (NPV) of five cost terms each weighted by a certain relevance factor. The considered cost terms include the total investment cost, the total cost of maintenance, consumed energy, unserved energy and emissions in the system all under the assumption of perpetual planning horizon.

As already mentioned, in the formulation is employed one of the concepts most used in the investment study in the financial world, the Net Present Value, which conceptually shows how to value in monetary terms the cash flows in any investment planning, in this case, considering the costs associated with the expansion planning of a given system.

This model will be tested in Chapter 5 on a case study and the further numerical results will be discussed there.

Chapter 4

Problem Formulation and Solution - Genetic Algorithms Approach

In this chapter, a method to investigate the impacts of network switching as well as installing DGs in distribution system is presented. To carry out this analysis, different models are formulated. A brief description of the genetic algorithm employed is presented in this chapter.

4.1 – An overview of Genetic Algorithms

Genetic algorithms are nature-inspired solution algorithms often suited for complex and combinatorial problems [72] . Such algorithms are based on natural selection and genetic mechanisms. They explore historic information to find points that are expected to lead to the best performance. This is done by an iterative process. Each iteration is often referred to as a generation. During each iteration, the principles of selection and reproduction are applied to a population. The selection process determines the individuals that will be reproduced (fathers), creating a determined number of descendants (sons) to the next generation by a determined probability named *fitness index*. This can be understood as the individuals with better relative adaptation, having greater chances to transmit their genes [73].

In a genetic algorithm, a possible population of solutions progresses according to the genetic operators (probabilistic) conceived by biological representations. On average, there is a tendency to have better solutions as the evolutionary process lasts. Notwithstanding, genetic algorithm exploits a probabilistic and metaheuristic method to obtain new populations. It is not a random solution search algorithm because it explores the available information to search new individuals or better solutions to improve a performance index.

Genetic algorithms seek to privilege individuals with better skills. By this means, they try to drive to regions of search space where global optima are located. Sometimes, this cannot be achieved if the parameters are not well suited for the problem.

4.1.1 -Codification

The basis to a genetic algorithm application to a problem is the representation of the problem to be analyzed. Each representation must have matching genetic operators. This is critical for genetic algorithms to operate correctly to the correspondingly optimization problem.

Genetic algorithm creates populations of individuals. This is called a chromosome, a data structure. Generally, chromosomes are vectors or binary values chain, reals or combinations of both. A chromosome represents a possible solution to the problem. Hence, a chromosome forms the set of parameters of the objective function that will be optimized. All the configurations that a chromosome can assume is called a search space. If a chromosome has n parameters of a function, it will be a search space with n dimensions. The majority of representations are genotypic Genotype is the set of genes that defines the genetic constitution of an individual. Genetic operators will be applied to genes [72]. Genotypes are represented by finite scale vectors, that the user needs to specify (see in Figure 4.1).

The genotype of an individual is conventionally represented by a binary vector. Each element of the vector characterizes a certain characteristic relevant to the construction of a unique individual. Combinations of elements can form the real characteristics of an individual, namely its phenotype. This representation is problem independent because once found the representation in binary vectors, standard operations can be applied, helping the employing in different classes of problems. Binary representation is the most commonly used approach because it is easy to implement, manipulate and analyze. But if the problem has continuous parameters, chromosomes could have bigger representations if the user wants to work with a higher precision. This leads to the use of a larger amount of memory. The majority of genetic algorithms proposed in the literature have a fixed number of individuals in a population, with constant size chromosomes. This is the simplest method to create a population of individuals [73].

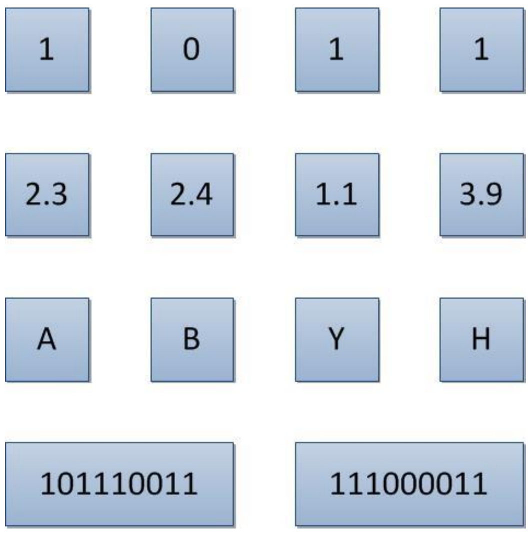

Figure 4.1 – Possible chromosome representation.

Having defined the chromosomic representation to the problem, a possible set of solutions are generated called aspirants. These aspirants are normally called sons due to the fact that they have a genetic material from their fathers. The set of codified solutions according the selected representation matches a population of individuals representing, over the evolution cycles, the current stage of problem solution. In each iteration, the population is modified because genetic algorithms involve an iterative process. Each iteration is called a generation although not all population individuals are necessarily sons of individuals of the population in the preceding iteration.

In the populations, several statistical values are calculated that will be used to evaluate if the search is close to the optimal solution. Parameters that can be evaluated are the best individual, diversity, standard deviation and average of accomplished goals. Normally, the evaluation is done to the objective function, this is the simplest way. This is simply to say that objective function becomes the fitness function, and there is no need to calculate the relative fitness function.

4.1.2 -Initialization

The representation of a search space is the most sensitive issue. Hence, initialization leads to some mechanism of making educated guess. The types of initializations are the following [74]:

- Random initialization – Individuals of the population are generated randomly.
- Deterministic initialization – Individuals of the population are generated deterministically by heuristic methods.
- Random initialization with niche – Individuals of the population are generated by ways that can be divided in species. This will group individuals with similar characteristics.

Randomly initializing population of n individuals are generated or some heuristic methods are used. This is the classic initialization that can be found in most relevant works. Without variety, there is no evolution. The natural selection theory (Darwin's Theory of Evolution) implies individuals that have different adaptation index to the ambient where they live, so it is important to have a large search space in the genetic algorithm.

Initial population generation can be obtained obeying some conditions established by the user. The user can establish such conditions from previous knowledge of the problem. The more restrictive these conditions are, the faster the convergence is. This is because the generated values are closer to the desired (possibly optimal) solution. There is no formula to the number of individuals that compose the population. They can be dependent on some heuristics but it's more reliant on the user's experience, and his/her previous knowledge of the objective function. The larger the number of individuals is, the higher the probability of convergence because the probability of the solution among the elements of population is bigger. But this may lead to greater computational effort, increasing the computation time. If the population is too small, it will not have diversity, the search space is reduced and the convergence will be premature.

The objective is to generate a population within a certain interval where it could be the solution. With this, it is not necessary to generate a random population. In the current work, we know that the number of branches must be equal to the number of buses minus the number of generators to keep radial configuration of the DNS, consequently, we can generate a uniform distribution between this fixed number of branches and zero.

4.1.3 -Evaluation

A genetic algorithm needs information about the value of the objective function to each individual of the population. The objective function gives the measure of how good the individual is adapted to the environment. In other words, this relates to the probability to survive and reproduce, transferring its genetic material to the next generations. The evaluation of the individual results in the so called "fitness function"[74].

Validating is the next step and it can be defined as the process to compare the fitness function from all individuals and sorting them out by their corresponding fitness function values. Normally, the best/bests are selected, according to the evolution theory. Convergence and the performance of the population related to the objective function is analyzed. This can be done by calculating the maximum, minimum and average of the fitness function or the standard deviation in each generation. Convergence can be a process of setting a finite number of generations (the most practical way).

If the initial population happens to have the exact solution to the problem, the algorithm will not stop. Convergence of the algorithm is achieved only, for instance, when the average fitness of the population is well stabilized or we reach the maximum number of generations. This can indicate that the population is adapted to the environment and the elements lead to the best objective function value. This can also indicate that we are stuck in an optimum location and need to improve the search space. The best individual is saved whether it belongs to the actual population or not. In the end, this will be the expected result. The recording is always done in each generation to see if we reached the optimum solution.

In genetic algorithms, convergence can be very fast to a sub-optimal solution. This is not what is desired, however. This problem is called premature convergence and it can occur by a small population or badly distribution of initial population. Premature convergence can occur due to bad distribution of individuals in search space and will affect the search for the global optimum. Such a premature convergence is also called diversity loss. Diversity indicates the rate which each region is represented in the solution search space. This can be overcome by improving the distribution of individuals in the initial population and preventing loss of diversity in the first generations. In addition, increasing the number of individuals will improve the search space. The selection process will guarantee that the best individual will dominate the next generation and so on if there are no better individuals with a best fitness function.

4.1.4 -Selection

Selection is the process that will make the initial population more fit after many generations. This is the basic principle of genetic algorithms. Selection mechanism in genetic algorithms tries to imitate the natural selection process [73], [74].

Genetic algorithms start with an initial population with a set of individuals. If we know a priori where the solution is located, the first individuals can be initialized deterministically. When we do not know anything about the search space, the individuals are created randomly. Deterministic way can lead us to fast convergence because the global optimum can be in the first generation. The selection process favors the fit individuals, and to a fitness function is assigned to each individual. This function is an input that represents the genes of the chromosome and provides their fitness as an outcome. Fitness is like a grade where the evaluation is made by a solution coded from each individual. This fitness is based on the objective function.

A relative fitness can be calculated to each individual. To some selection methods, it is desirable that the value of relative fitness for each individual be less than 1 and that the sum of every fitness values are equal to 1. The relative fitness of each individual is calculated by dividing its value of fitness (objective function that the solution from the individual) by the sum of values of the fitness of the entire individuals of the population (the sum of the objective functions of each individual). This is expressed by equation (4.1).

$$f(x_i)_{rel} = \frac{f(x_i)}{\sum_{j=1}^{n} f(x_j)} \tag{4.1}$$

where $f(x_i)$ is the fitness function.

Generally, a population of *n* individuals is generated with a probability proportional to its relative fitness in the population. Using the previous probability, we select *n* individuals. Individuals with low fitness will have high probability to disappear from the population. Individuals with high fitness will be passed on to the next generation. It is not necessary to calculate this fitness function because when we have a fixed maximum generation, we can analyze the objective function of each individual and select the best. This fitness function is a good instrument when we have convergence by some other method than a fixed number of generations (like average fitness of the population is well stabilized).

The objective function gives information about how close or far the solution is from the desired solution. It includes restrictions that need to be satisfied by the solution. In optimization problems, the objective function can be maximization or minimization of the objective function. It can be maximization of profit or minimization of costs. Some problems can include more than one objective function. Problems called multi-objective optimization can have an objective function that includes more than one objective.

The selection process chooses a subassembly of individuals based on fitness, creating an intermediate population. Different selection methods are implemented in genetic algorithms. Most of all seek to favor the fittest individuals in order to keep population diversity. Some methods are:

- Roulette;
- Tournament;
- Stochastic sampling;
- Classification.

The Roulette method is the simplest and the most commonly used approach. Individuals of the generation are selected to the next generation using roulette as we see in the famous game of casinos roulette wheel. Each individual is represented in the roulette according to their fitness value. This way, individuals with nice fitness get a bigger interval in the roulette and the others with low fitness will receive a shorter interval. After distribution in the roulette, certain values are randomly generated in the interval from 0 to the total summary of the fitness of all individuals, a determined number of times depending on the size of population. If a given individual is in the interval, the generated value will be selected to the intermediate population.

In tournament selection, *n* individuals of population are selected randomly with the same probability. The individual with the greatest fitness among them is selected to the intermediate population. Process ends when the intermediate population is fulfilled.

A stochastic sampling is a variation of Roulette method but instead of one unique needle, *n* needles equally spaced are used, where *n* is the number of individuals to be selected. This way, instead of spinning the roulette n times, it is only spinned one time.

A classification method primary classifies the population, then, each individual gets a grade according to the classification of the population. The worst individual will get the lower value that we can assign, the second worst gets the second worst value and successively. The best will get the highest grade, that can be equal to the number of individuals in the population. After the classification process, every individual has a certain chance to be selected.

4.1.5 -Genetic Operators

Global optimization algorithm must be capable of exploring new points inside the solution search space. This mechanism is called exploration and exploitation, and is often adopted in genetic algorithms by applying correct genetic operators. The main genetic operators are crossover and mutation primarily in a binary codification [75].

Crossover uses information in two or more individuals (fathers) to generate one or more individuals (sons). This can be resistant to add new information to population because it sees the region close to father's individuals. The process of recombination is a sexual process – it is more than one individual – and stimulates the exchange of information between chromosome pairs. It is a random process with a fixed probability that needs to be specified by the user.

Mutation can be a diversifier or booster to the solution search. Some approaches use mutation as the technique responsible for the evolution process, for determining if the movement is exploration or exploitation, and the adaptable parameters in each generation. Mutation can diversify when new information is introduced in the individual, and consequently to the population (very strong mutation). If the mutation is very weak, it is a booster in neighbor solution search. This process is equivalent to the random search. One position is selected in the chromosome, and changes the correspondent value to another random one. This can be controlled with a fixed parameter that indicates the probability of a gene suffering mutation.

Crossover and mutation can be combined to upgrade the search for the optimal solution by taking advantages of the best features in each method.

4.1.6 -Genetic Parameters

The performance of a genetic algorithm is strongly dependent on how the parameters to be employed are defined. Hence, it is important to investigate which way some parameters can influence in the behavior of the algorithm [76]. This way, we can establish the parameters according to the requirements and resources available. Parameters usually are size of population, crossover rate, mutation rate, substitution rate and convergence condition. Size of the population affects the global performance and efficiency of genetic algorithms. With a small population, the performance may drop because a relatively small search space is covered. Bigger population offers a representative search space domain and avoids optimum local solutions. However, to work with bigger populations, we may need a longer simulation time or more computation resources.

Crossover rate specifies how fast new structures are introduced in the population. If it is set very high, good structures can be removed faster than the selection capacity. With a small rate, the algorithm can become slow or stagnate. Mutation rate prevents that the search becomes stagnated in regions of search space. It allows that every space search point can be achieved. With a high rate, the search becomes random.

Substitution rate controls the population percentage that will be substituted in the next generation. With a higher rate value, most of the population will be substituted but it can suffer of losing great structures of fitness. When the rate value is too low, the algorithm may become slow. Substitution rate is not commonly used because with a nice mutation and crossover rate, we can guarantee that the next generations will be always better than the previous ones.

A convergence condition is the condition when the algorithm will stop. The ideal is to stop when we reach the optimum solution in an optimization problem. When we have multimodal functions (saddle points, with many optimal points and one global optimum) it can be sufficient when we reach one optimal point but there are situations where the largest possible number of optimal points is desired. In practical, we cannot tell with certain if a given point matches the global optimum. As a consequence, it’s used as convergence condition a maximum number of generations or a limit of computational time to stop the algorithm. Another criterion is to stop the algorithm if during several generations the fitness function is not getting better, interpreted as an idea of stagnation of the solution.

4.2 – Genetic Algorithms: Formulation

In this work, a GA is used to solve the resulting problems based on AC OPF models. The OPF problems are solved using the MatPower toolbox in MATLAB environment. MatPower is a package of MATLAB for solving power flow and optimal power flow problems. It is intended as a simulation tool for researchers and educators that is easy to use and modify.

A GA is a method for solving constrained and unconstrained problems optimization problems, particularly suited for non-linear and combinatorial problems. It is based on natural selection. The process that guides a GA is basically initialization, mutation, evaluation and selection. In this work, a GA is employed to solve the reconfiguration of distribution system as wells as placement and sizing of DGs. The implementation process of the GA is summarized as follows:

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- Step 1: Initialization – Generate the set of branches and set of DG's in each node
- Step 2: Mutation – Mutate the chromosome of branches and DG's
- Step 3: Evaluation - Check the radially constraints
- Step 4: Run the OPF of radial populations
- Step 5: Selection
- Step 6: Uniform Crossover and a Small Mutation - Crossover and Small mutation for a new population based on the best populations.
- Step 7: Selection – Select the best population.

The chromosome of the set of branches connected is binary, 1 if connected and 0 if disconnected. The generation of radial populations is based on number of buses minus the number of generators. The DG placement does not affect this stipulation. The algorithm used is shown in Figure 4.2.

The DG chromosome is generated by integer numbers between 0 and 4, respecting the size of DG in MW and with a length of number of buses. This way we generate the location and size of DG. The parameters of the network are introduced in a MatPower case. To solve the OPF, we just need to pass to the MatPower information regarding the statuses of the branches.

The DGs are regarded as a PV bus. Hence, in order to solve the OPF, we need to introduce the generator data and the generator cost data. Running the OPF, we obtain the voltage profile, costs and line flows.

First, we will investigate the benefits of having only reconfiguration in the system. Second, we will solve the problem of DG placement and sizing along with the reconfiguration problem. This way, the best places to install DG's and their optimal size, as well the network topology is determined.

The objective function is the total costs in the system. This will be our fitness function that needs to be minimized.

In order to get the best topology, we penalize the configurations that do not lead to radial configurations. Then, if it fulfils the radially constraints, we check if all buses are connected. If not, another penalization is introduced. After running the OPF and see if it converges, investigation regarding voltage limits is done. If the voltage limits are not respected, another penalization is introduced in the fitness function. If the OPF does not converge, we penalize the fitness. This will lead to the best cases.

This process is also reproduced when we introduce DGs in the problem. A DG is treated as another population and all the constraints regarding the OPF will be checked and respected. Different costs of DG are considered in order to seek for the best cases.

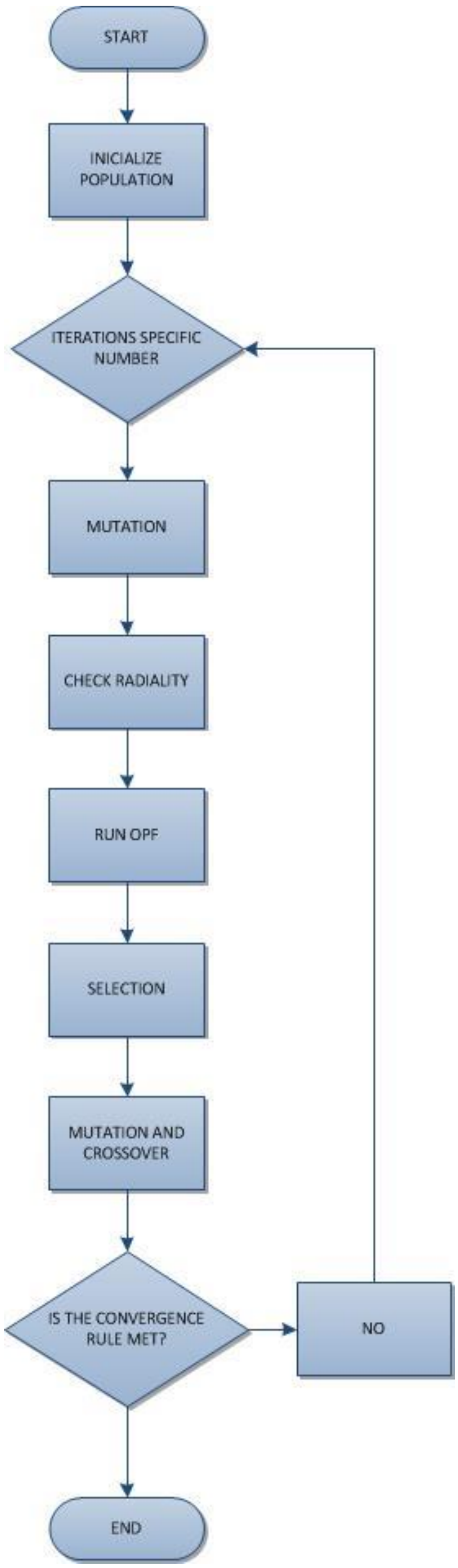

Figure 4.2 - Flow Chart of the proposed GA.

4.3 – Summary

In this chapter, an overview of the genetic algorithm (GA), the optimization problems and the solution procedures have been described. Overall, the problem considered in the optimization process jointly takes into account the optimal DGs placement and size in coordination with distribution network switching in one operation scenario.

The resulting problem has been solved using a genetic algorithm, where a brute-force AC OPF is considered with an objective of overall cost minimization. The objective function is composed of costs related to power production in one operation scenario. In addition, loss minimization has been taken into consideration with reconfiguration of the distribution system.

Chapter 5

Case Studies, Results and Discussion

5.1 - Mixed Integer Linear Programming based Optimization

5.1.1 – Case Study: A 33-bus Test System

A standard IEEE 33-bus radial distribution network, shown in Figure 5.1, is used here for carrying out the required analysis mentioned earlier. The system has a rated voltage of 12.66 kV, and a total demand of 3.715 MW and 2.3 MVAr. Network data and other related information about this test system can be found in [77]. Other data and assumptions made throughout this paper are as follows:

- The planning horizon is 3 years long, which is divided into yearly planning stages, and a fixed interest rate of 7% is used.
- The expected lifetime of ESS is assumed to be 15 years while that of DGs and feeders is 25 years.
- Two investment options with installed capacities of 0.5 and 1.0 MVA are considered for each wind and solar PV type DG units.
- The installation cost and emission related data of these DG units, provided in [78], are used here.
- For the sake of simplicity, all maintenance costs of DGs are assumed to be 2% of the corresponding investment costs while that of feeders is 450 €/km/year.
- The investment cost of each feeder is 38700 €/km.
- The current limits of all feeders is assumed to be 200 A except for those between nodes 1 and 9 which is 400 A.
- It is assumed that all feeders can be switched on/off, if deemed necessary
- In addition, it is assumed that wind and solar power sources are uniformly available at every node.
- The cost of energy storage is 1000k€/MW;

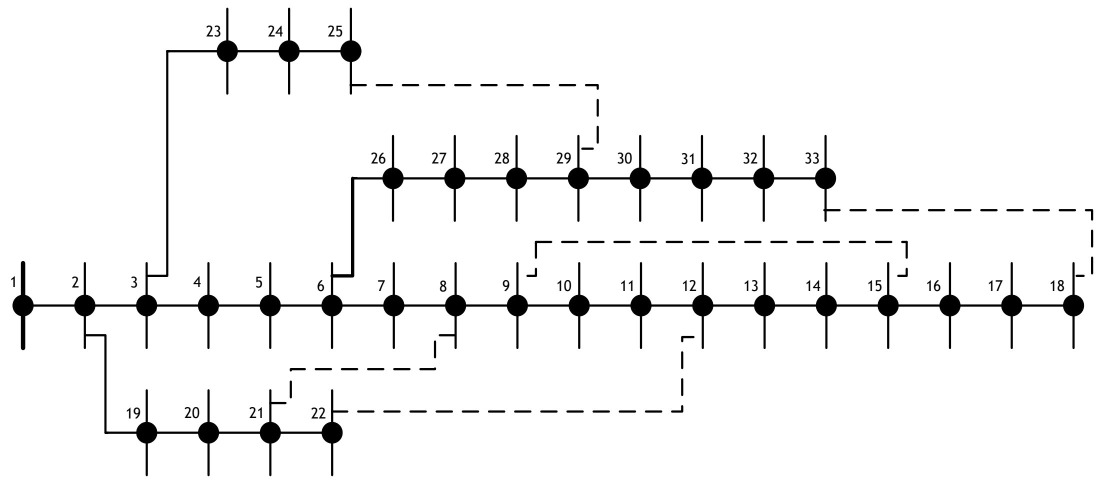

Figure 5.1 - 33-bus radial distribution system.

- The operational variability and uncertainty introduced by wind and solar PV type DGs, demand and electricity price are accounted for via the clustering method proposed in [79].
- The maximum allowable bus voltage deviation in the system is set to 5%, and node 1 is considered as a reference with a voltage magnitude of 1.0. Annual demand growths of 0%, 5% and 10% are also considered in all simulations.
- Emission prices in the first, second and third stages are set to 25, 45 and 60 €/tCO2e, respectively, and the emission rate of power purchased from upstream is arbitrarily set to 0.4 tCO2e/MWh.
- The cost of unserved energy is 2000 €/MWh. A power factor of 0.9 is considered in the system, and is assumed to be the same throughout. The base power is set to 1 MVA.
-

The computed values of relevant variables are analyzed for different cases (as depicted in Table 5.1) over the three years planning horizon. Case 1 represents the base case topology where no investments are made while Case 2 considers an optimal reconfiguration but with no investments. Cases 3 and 4 both consider investments in DGs only but differ in that the former does not change the network topology and the latter uses optimal switching. The last two cases correspond to scenarios where investments in DGs are coordinated with that of ESSs. Case 5 uses the topology in the base-case while Case 6 uses network reconfiguration.

5.1.2 – Results and Discussion

The results in Table 5.1 reveal the significant differences in overall NPV cost in the system, share of energy supplied by RES and ESS combined, cost of total network losses and unserved power among the aforementioned cases. The results are also compared with the base case system where no investments are made and the network topology is held the same. Network reconfiguration alone, as in Case 2, results in about 8.4% in the cost of losses, and a 3.1% reduction in the NPV overall system cost compared with that of Case 1. In addition, network reconfiguration avoids a total of 396.3 kVA load curtailment (or 256.9 kVA in Case 3) that would otherwise occur at nodes 17, 18, 32 and 33 due to voltage limit constraints in Case 1.

Table 5.1 - Results of Relevant Variables for Different Cases.

Cases	Total cost (TC) [k€]	Energy supplied by RES and ESS [%]	Total cost of losses [k€]	Total cost of unserved power [k€]	Total installed size [p.u.]		
					Wind	Solar	ESS
1	45447.91	0.0	1089.80	1505.70	0.0	0.0	0.0
2	44044.58	0.0	997.85	0.00	0.0	0.0	0.0
3	33281.50	58.1	433.58	161.79	6.0	3.0	0.0
4	33106.07	58.2	404.59	0.00	6.0	3.0	0.0
5	26522.10	88.8	218.33	0.00	8.0	1.0	3.0
6	26516.52	88.8	212.73	0.00	8.0	1.0	3.0

Another more interesting observation from Table 5.1 is that Cases 3 and 4 result in (approximately) 60% reductions in the overall cost of the system and the amount of imported energy. Wind and solar power sources are complementary by nature. This important phenomenon seems to be exploited when DG investments are not accompanied by investments in ESSs (i.e. Cases 3 and 4). This is because, according to the DG investment solution in Table 5.1, the operational variability in the system seems to be handled by investing an appreciable amount in both complementary power sources (wind and solar). This can also be seen from the level of demand covered by RESs, which is about 58%.

The results corresponding to Cases 5 and 6 show that the total cost and cost of losses are dramatically reduced by more than 41.6% and 80% respectively. This reveals the substantial benefits of coordinating investments DG with ESSs. Generally, ESSs significantly improve system flexibility, enabling large-scale accommodation RES energy. Interestingly, the total amount of installed DGs (9 MW) is the same for Cases 3—6 i.e. with/without ESSs. Even if this is the case, in the absence of ESSs (Cases 3 and 4), there may be spillage of RES power when the demand is lower than the total generated power. However, the installation of ESSs leads to an efficient utilization of RES power. This is evident from the amount of energy consumption covered by the combined energy supplied by RESs and ESSs in Cases 5 and 6 is about 89%.

Normally, network switching capability also improves system flexibility, leading to a high level RES penetration. In this particular study, the effect of network switching on the level of RES power absorbed by the system is not significant as one can observe in Table 5.1. This may however be case-dependent. A more frequent switching capability could, for instance, have significant impact.

The optimal location and size of installed DGs corresponding to Cases 3 through 6 is shown in Figure 5.2. The average voltage profiles at each node and for each case are depicted in Figure 5.3. It is interesting to see in this figure the substantial contributions of DGs and ESS installations to voltage profile improvement.

As shown in Figure 5.3, the coordinated integration of DGs and ESSs (i.e. Case 6), especially leads to the best voltage profile. Figure 5.4 demonstrates the optimal network topology, DG and ESS locations corresponding to this case. The nodes 8, 14, 25, 30 and 32 are within the 4 cases. We can assume that these nodes possibly are the critical nodes to invest. The benefit of joint DG and ESS investments along with network reconfiguration in terms of losses reduction (over 84% on average) can be seen from figure 5.5. The spikes observed in Case 6 are because of the variability in RES power injected into the system.

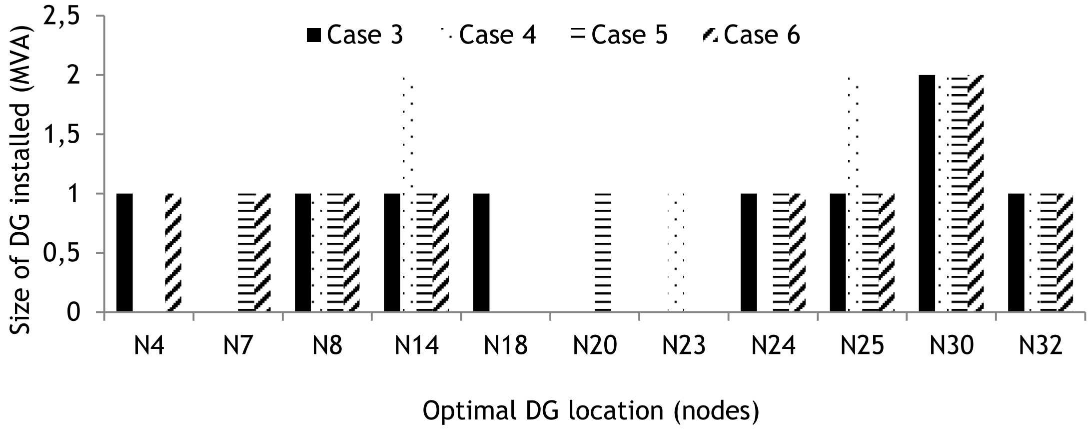

Figure 5.2 - Optimal DG location in Cases 3, 4, 5 and 6.

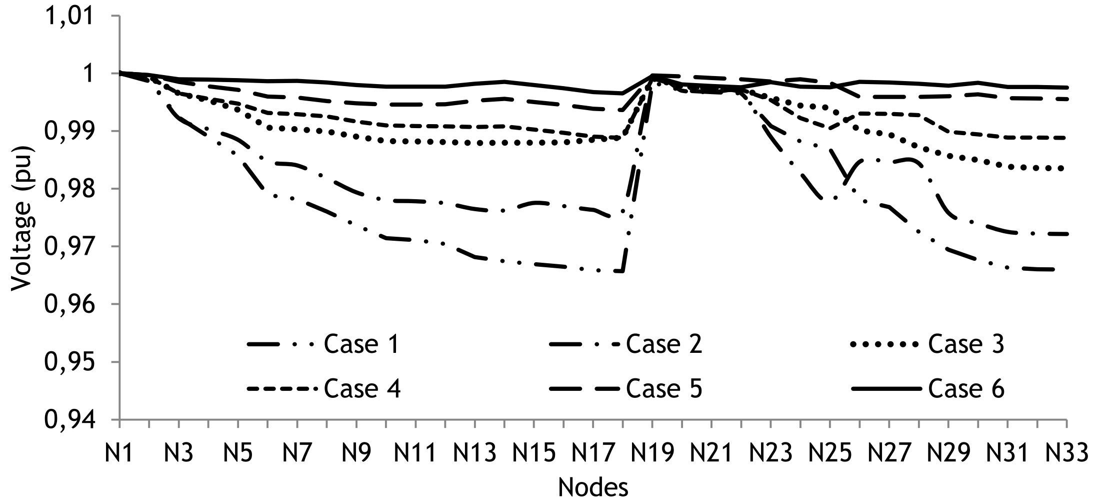

Figure 5.3 - Average voltage profiles in the system under different cases.

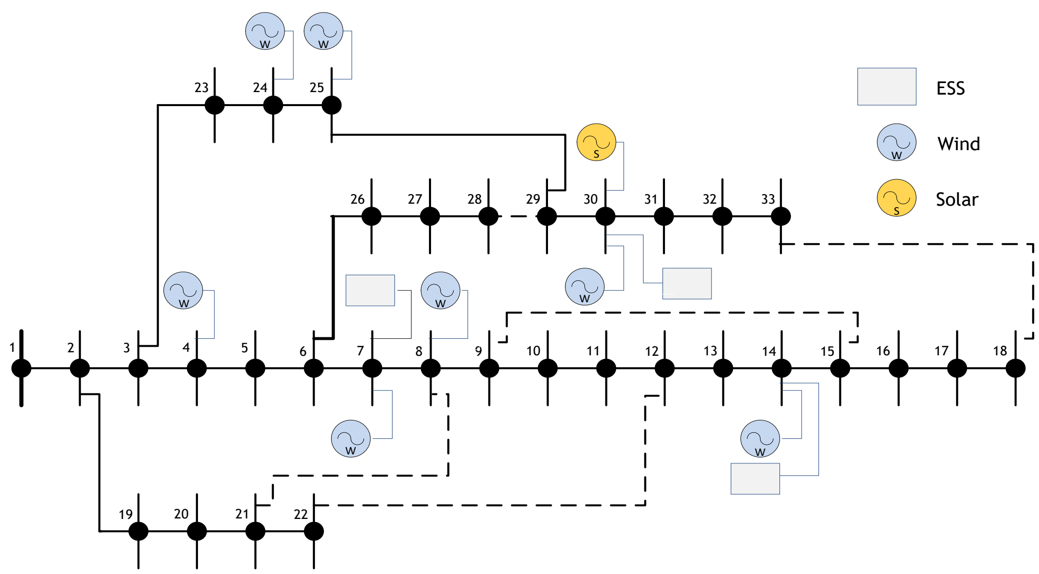

Figure 5.4 - Optimal locations of DGs and ESSs under Case 6
(Opened switches 28-29, 8-21, 9-15, 18-33, 12-22).

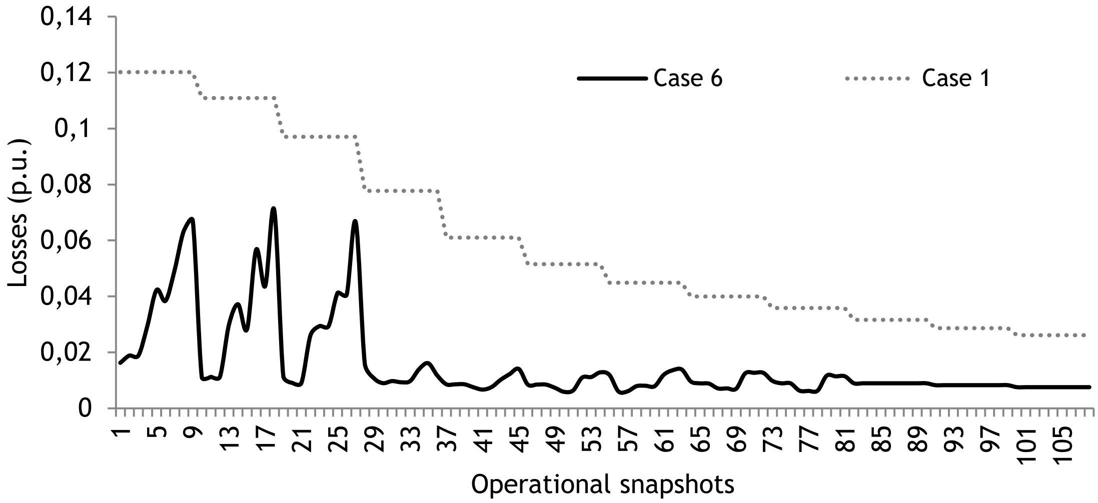

Figure 5.5 - Total system losses profile.

As shown in Figure 5.3, the coordinated integration of DGs and ESSs (i.e. Case 6), especially leads to the best voltage profile. Figure 5.4 demonstrates the optimal network topology, DG and ESS locations corresponding to this case. The nodes 8, 14, 25, 30 and 32 are within the 4 cases. We can assume that these nodes possibly are the critical nodes to invest. The benefit of joint DG and ESS investments along with network reconfiguration in terms of losses reduction (over 84% on average) can be seen from figure 5.5. The spikes observed in Case 6 are because of the variability in RES power injected into the system.

5.2 - Genetic Algorithm Results

5.2.1 - Case Study: 16-bus Test System

Figure 5.6 shows the 16-bus test system used for analysis of the results from GA. The system has a rated voltage of 23 kV and a total demand of 28.7 MW and 17.3 Mvar. The maximum allowable bus voltage deviation in the system is set to 5%. A power factor of 0.95 is considered for the DG. The costs of the generators at the feeders are given by polynomial functions, and two options are considered as in (5.1) and (5.2):

$$C(P) = 150 + 20P + 0.01P^2 \text{ €/h} \tag{5.1}$$

$$C(P) = 180 + 30P + 0.03P^2 \text{ €/h} \tag{5.2}$$

For integrating the DG as a PV bus and add to the cost of the system given by the OPF, one polynomial function (5.3) was taken in consideration.

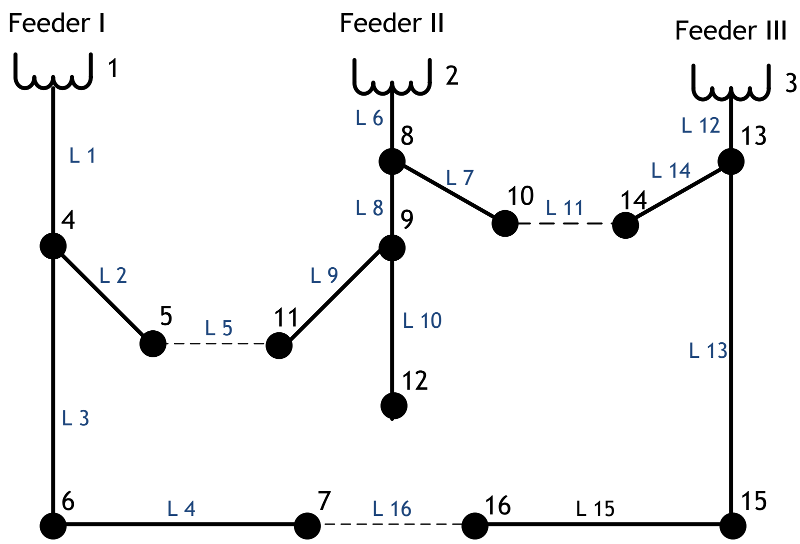

Figure 5.6 - 16-bus radial distribution system [67].

$$C(P) = 8P \text{ €/h} \tag{5.3}$$

It is assumed that DG power sources are uniformly available at every node. Nodes 1, 2 and 3 are considered as references. The base power is set to 1 MVA. Network data and other related information about this test system can be found in [80]. The variations of different relevant parameters when considering different cases (as depicted in Table 5.2) are analyzed.

- Case 1 represents the base case with the 3 feeders having the same costs
- Case 2 considers reconfiguration of the base case
- Case 3 refers to the base case reconfiguration but with different generation costs at the feeders
- Case 4 considers reconfiguration with different costs for feeders;
- Cases 5 and 6 denote scenarios where, instead of minimization of costs, we minimize the losses but they differ in the costs of feeders that are different in Case 6
- Case 7 considers the reconfiguration with DG capable of injecting and absorbing active and reactive power
- Case 8 considers reconfiguration with DG capable of injecting and absorbing active power
- Case 9 considers reconfiguration with DG capable of injecting and absorbing reactive power

In Cases 3, 4 and 6, three scenarios for different costs are proposed: 1) the generator at feeder 1 (F1) is more expensive, 2) the generator at feeder 2 (F2) is more expensive, 3) the generator at feeder 3 (F3) is more expensive.

5.2.2 – Results and Discussion of the 16-bus Test System

The results in Table 5.2 reveal significant differences in overall operation costs, active and reactive power losses and total installed size of DGs. Network reconfiguration, Case 2, compared with base case, Case 1, results in about 0.04% of reduction in total cost, a 7.17% reduction in total active power losses and a 5.98% reduction in total reactive power losses. Topology from Case 2 is shown in figure 5.7. The voltage profile can be seen in Figure 5.8. The improvement in voltage profile is appreciable. Table 5.3 summarizes the numerical results concerning the network topology (opened branches) along with the DG location and size. Comparing the costs corresponding to different generation cost assumptions at the feeders, i.e. Case 4 with Case 3, there are some relevant issues worth mentioning here. The first one is that the costs are lower in Case 4 than in Case 3, but we get higher values of losses. This may be due to the fact that the reconfiguration tries to find the path that minimizes the involvement of the more expensive feeder. We can see in Figure 5.9 that the feeder is always with one bus, feeding the demand. We will get a feeder that will be feeding more buses and the losses will increase comparing the cases that are related. All the scenarios in Case 6 have the same configuration, that is the same configuration of the Case 2. This configuration is illustrated in Figure 5.7. In addition, in Case 6, the scenarios seem to lead to high total costs except in 6-F2. This shows that the single reconfiguration of the system is different if we are considering minimization of losses or minimization of costs.

In Figure 5.10, we see that the voltage profile for case 4-F2 is worse than the case 3-F2 despite having obtained the best costs in case 4-F2. This is because the topology of the network that leads to bigger losses, impacting the voltage profiles. The voltage profiles of Case 6 are the same as Case 2, and Figure 5.8 reveals this phenomenon.

Table 5.2 – Results of Relevant Variables for Different Cases.

Cases	Total Cost [€/h]	Total Active Power Losses [MW]	Total Reactive Power Losses [Mvar]	Total installed DG size [MVA]	Computation time [s]
1	1029.4177	0.1064	0.1224	0	-
2	1029.0201	0.0987	0.1151	0	7.848185
3-F1	1146.0389	0.1064	0.1224	0	-
3-F2	1215.8225	0.1064	0.1224	0	-
3-F3	1111.0366	0.1064	0.1224	0	-
4-F1	1081.0391	0.1510	0.1680	0	8.262878
4-F2	1100.7268	0.1480	0.1777	0	12.175396
4-F3	1070.4623	0.1251	0.1517	0	9.956841
5	1029.0201	0.0987	0.1151	0	7.540224
6-F1	1151.8748	0.0987	0.1151	0	6.644372
6-F2	1198.3556	0.0987	0.1151	0	11.134548
6-F3	1120.9084	0.0987	0.1151	0	9.013040
7	790.0860	0.0290	0.0311	21	24.246142
8	790.0860	0.0540	0.0583	16	30.989449
9	1028.8530	0.0927	0.1054	14	27.035288

Table 5.3 - Opened Branches and Location of DG.

Cases	Opened branches	DG Bus Location
1	5-11; 10-14; 7-16	-
2	8-10; 9-11; 7-16	-
3-F1	5-11; 10-14; 7-16	-
3-F2	5-11; 10-14; 7-16	-
3-F3	5-11; 10-14; 7-16	-
4-F1	4-5; 4-6; 8-10	-
4-F2	4-6; 8-9; 8-10	-
4-F3	9-11; 13-14; 13-15	-
5	8-10; 9-11; 7-16	-
6-F1	8-10; 9-11; 7-16	-
6-F2	8-10; 9-11; 7-16	-
6-F3	8-10; 9-11; 7-16	-
7	6-7; 9-11; 10-14	4; 5; 6; 7; 9 12; 15
8	6-7; 13-14; 5-11	5; 6; 11; 12; 13; 15
9	6-7; 8-10; 9-11	4; 6; 9; 15; 16

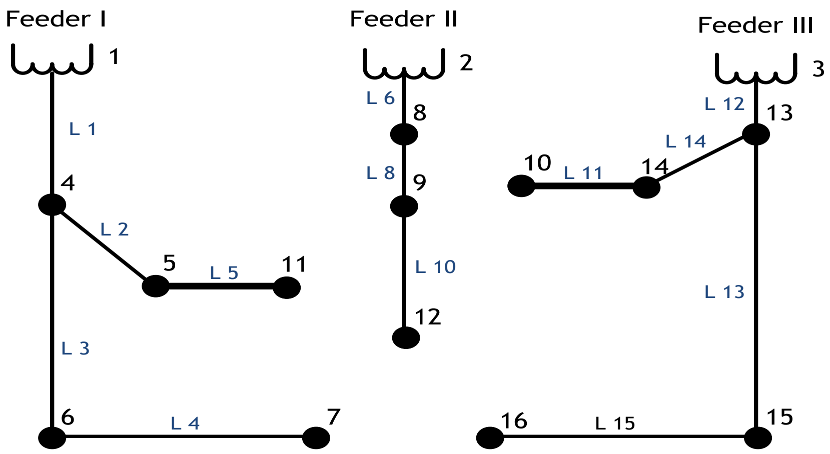

Figure 5.7 - New topology of the distribution system from Case 2.

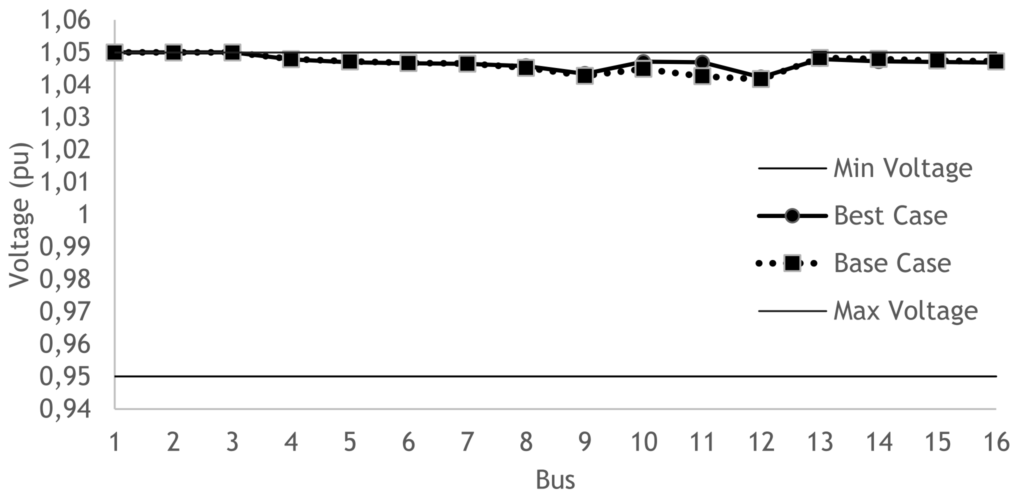

Figure 5.8 - Voltage comparison between base case and reconfiguration.

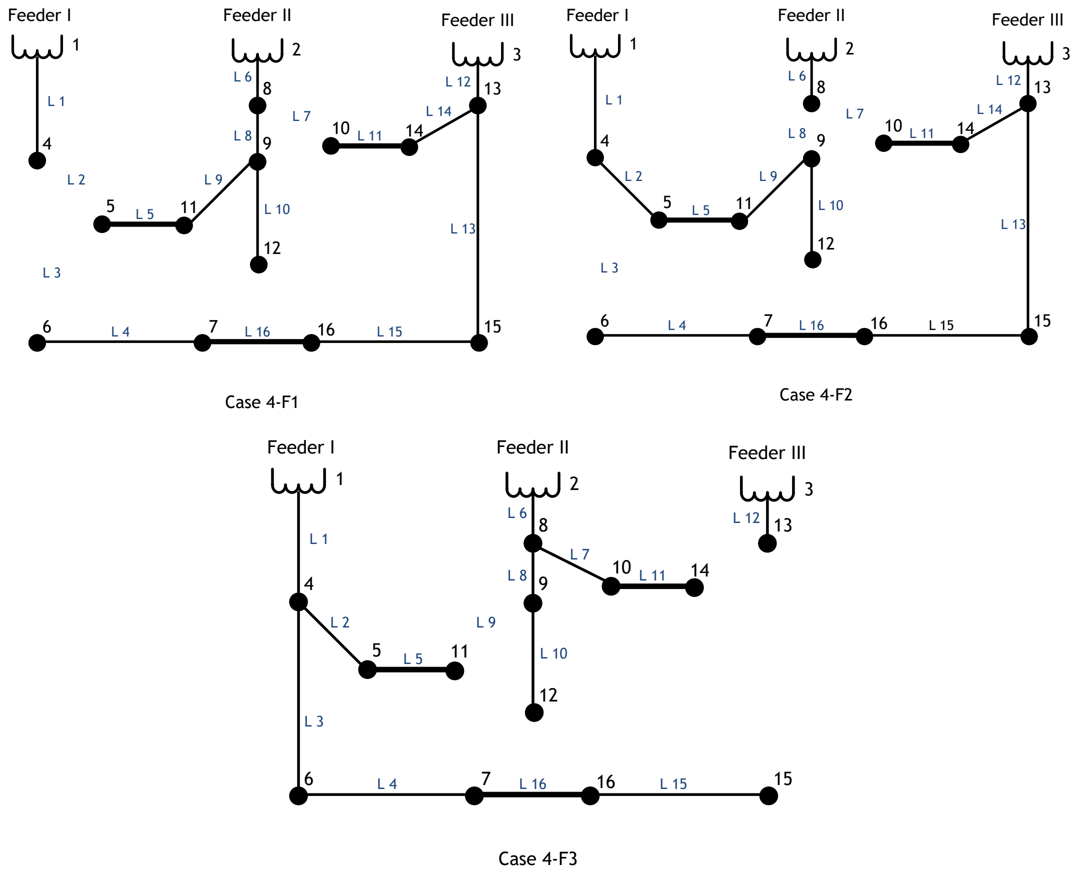

Figure 5.9 - Reconfiguration under different feeders cost.

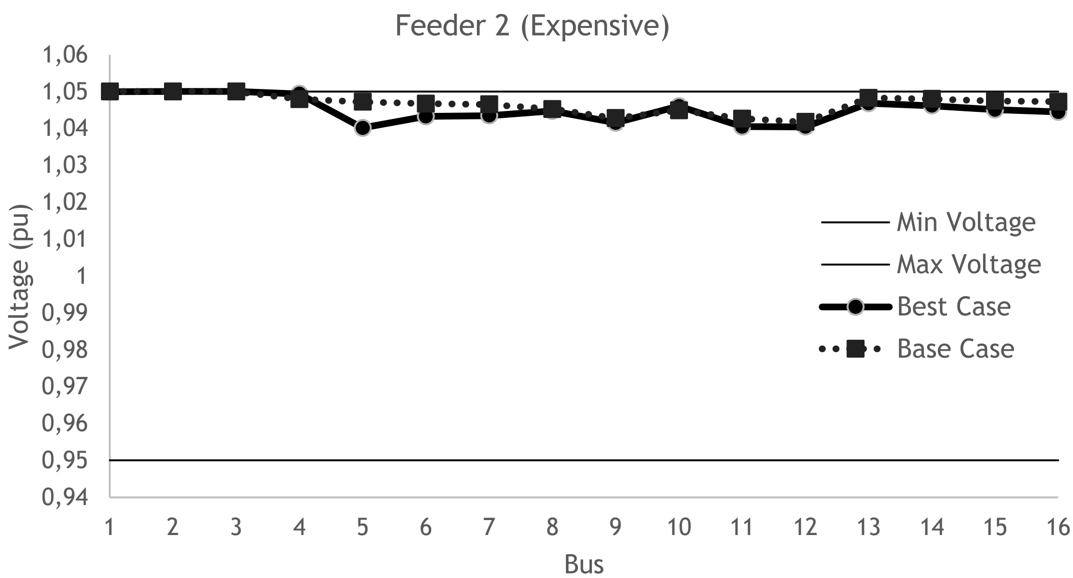

Figure 5.10 - Voltage profile of Case 4-F2.

When we analyze the Cases 7 through 9, we can observe some substantial differences. In case 7 and 8, where the DGs can control the active power, the total costs are the same. In Case 7, the total costs are reduced by 23.25% approximately, the active and reactive power losses are also slashed by 72.72% and 74.63%, respectively. Similarly, in Case 8, the total costs, active and reactive power losses are also approximately reduced by 23.25%, 49.27% and 52.40%, respectively. In Case 9, where DG can only control reactive power, the costs are only reduced by 0.05%, the reduction in active and reactive power losses is approximately 12.84% and 13.91% respectively.

The numerical results generally show the substantial benefits of integrating small distributed generation in the distribution network system, particularly in reducing costs and losses. As for voltage profile, it can be seen in Figure 5.11. We can see that there are improvements in the voltage profile across all nodes in the system. The introduction of DGs with reactive power support capabilities has a greater impact in total losses than installing DGs capable of supplying only active power or reactive power. The results strengthen this argument. In addition, the total installed size of DGs is in decreasing order from Case 7 to Case 9. This is because of the fact DGs with reactive power support capability significantly contribute to the controllability of the system, hence, resulting in a substantially reduced costs and losses. This in turn results in a more integration of DGs in the system. Figure 5.12 shows the optimal location of DGs and the configuration of the system under Case 7. In Figure 5.13 we can see the distribution of the DGs in the 16-bus distribution system. The nodes 6 and 15 are common in the solution. This solution can be interpreted as the nodes that can be critical to invest in DGs.

The total installed DGs covers about 70% of the required demand in Case 7, 53% in Case 8 and 46% in Case 9.

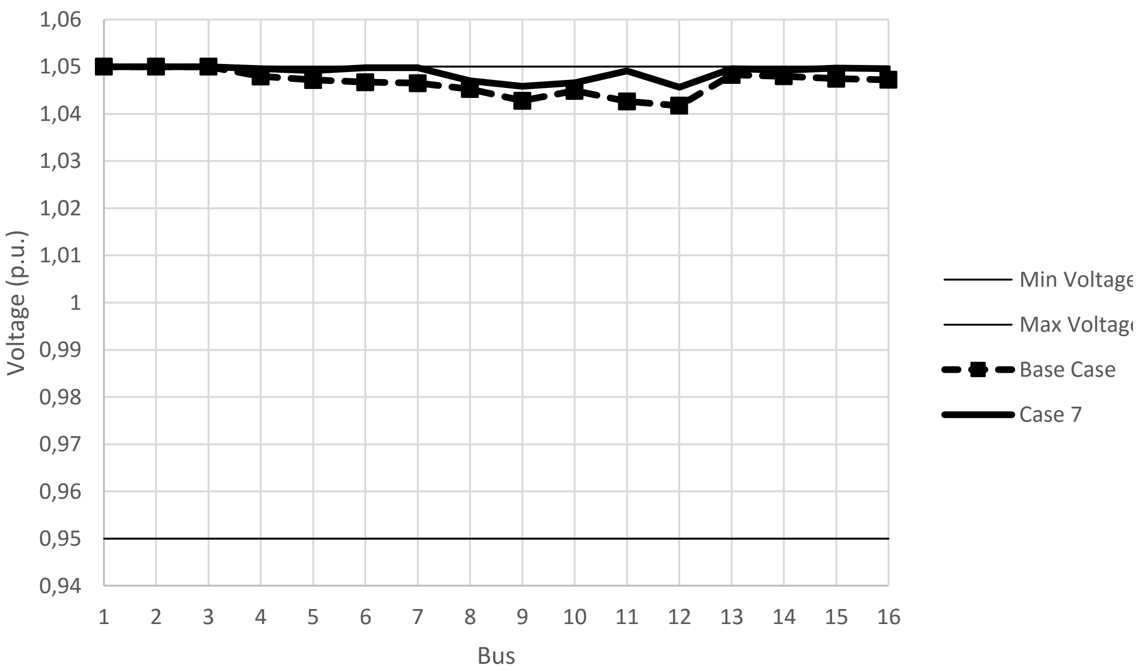

Figure 5.11 - Voltage comparison between Case 7 and Base Case

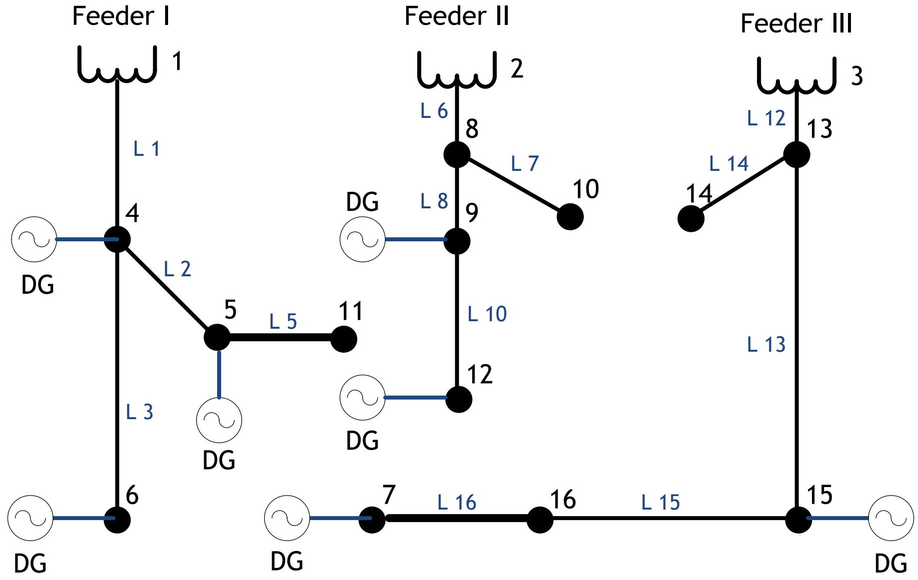

Figure 5.12 - Optimal location for DG and reconfiguration in Case 7.

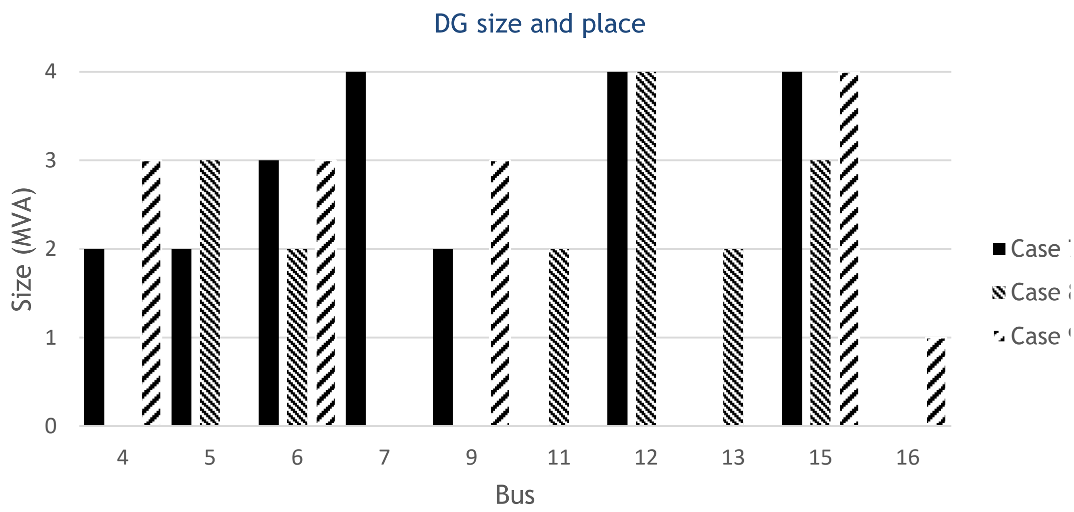

Figure 5.13 - Size and placement of DGs in the 16-bus distribution system.

In Figure 5.14, the convergence process is shown for Case 2. This is the best fitness function that we have in each generation. A fast convergence of the algorithm in the 16-bus radial distribution system is achieved. As this is a GA, we cannot be sure if this is the best solution. The difference between solutions in each generation is very small. In the first generation, the cost associated with the best solution amounts to 1030.3622 €/h and that of the final solution is 1029.0201 €/h.

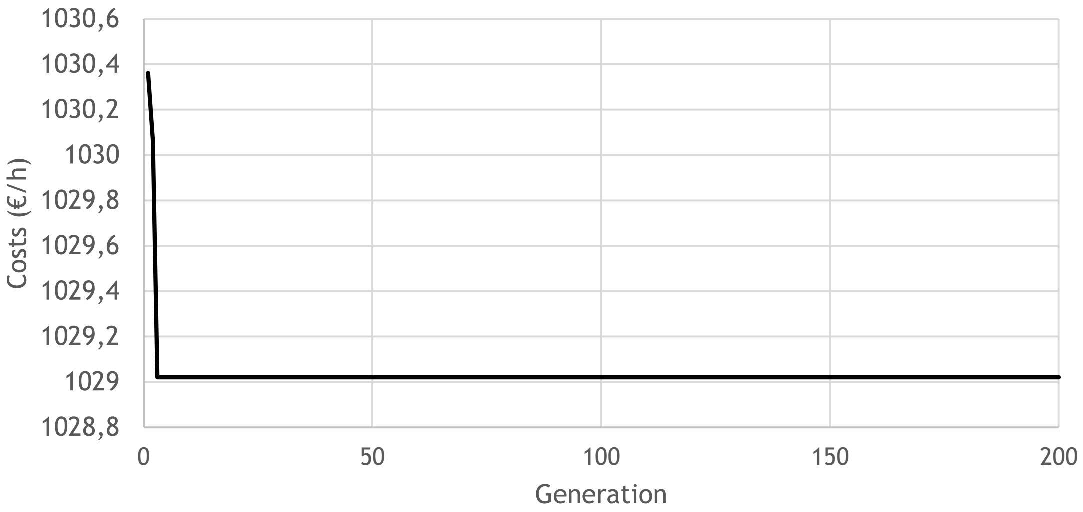

Figure 5.14 - Convergence process in Case 2.

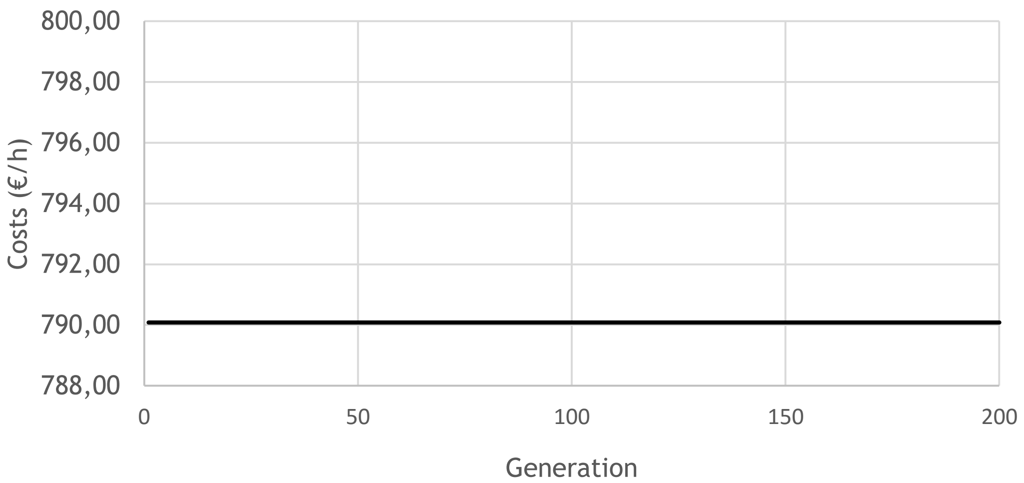

Figure 5.15 - Convergence process in Case 7.

The difference between these two solutions is about 0.13%. This is a very small deviation and shows the difficulty that we can have with the GA in achieving the optimal solution. In Case 7, we achieved the best solution in the first iteration but this is very rare, and may not be replicated in the same or other problems.

5.2.3 - Case Study: 33-bus Test System

In Figure 5.1 it is shown the 33-bus radial distribution system that was considered for carrying out the required analysis mentioned earlier. This case is already setup in *Matpower*. The system has a rated voltage of 12.66 kV, and a total demand of 3.715 MW and 2.3 Mvar. Network data and other related information about this test system can be found in [80]. The maximum allowable bus voltage deviation in the system is set to 5%.

A power factor of 0.95 is considered for the DG. The costs of the feeders are a polynomial function and two options are available (5.4) and (5.5).

$$C(P) = 150 + 20P + 0.01P^2 \text{ €/h} \tag{5.4}$$

For integrating the DG as a PV bus and add to the cost of the system given by the OPF, one polynomial function was taken in consideration:

$$C(P) = 8P \text{ €/h} \tag{5.5}$$

It is assumed that DG power sources are uniformly available at every node. Node 1 was It is assumed that DG power sources are uniformly available at every node. Node 1 is considered as the reference node. The base power is set to 100 MVA. The variations of different relevant parameters when considering different cases (as depicted in Table 5.4) are analyzed. Case 1 is the base case; Case 2 considers reconfiguration; Case 3 is a scenario where minimizes only losses. Cases 4, 5 and 6 all handle reconfiguration along with DG integration but they differ in that, in Case 4, the considered DGs are capable of producing active power as well as injecting and absorbing reactive power, Case 5 considers DGs that can only produce active power, and the DGs considered in Case 6 are capable of only producing or consuming reactive power.

5.2.4 – Results and Discussion of the 33-bus Test System

Comparing Case 1 with Case 2, we see that reconfiguration slightly lowers the total costs and losses. The total cost reduction is about 0.54%. The active and reactive power losses are also reduced by 61.59% and 17.38%, respectively. Like in the previous case studies, the results here show the benefits of reconfiguring the distribution network system. In Figure 5.16, the voltage profile of reconfiguration and the base case are shown. Clearly, the positive contribution of reconfiguration to the voltage profiles can be observed. The voltage is improved in almost all nodes, except in nodes 19, 20, 21 and 22. In addition, in Table 5.4, there is little difference between minimization of losses and minimization of costs, the difference is approximately 0.0057% for total costs, 0.5147% for active power losses and 0.5695% for reactive power losses. In Figure 5.17, we can see that the voltage profile is very similar. In Table 5.5, the unique difference between the opened branches is 9-11 in Case 2, and 10-11 in Case 3. Only one branch is different and almost leads to a similar fitness function value. As mentioned earlier, there is a small difference and we can conclude that these configurations are minimized but may not be the global optima. Further analyzing the results in Table 5.4, there is a significant difference in total costs and in total losses in Case 4 and Case 5 comparing to Cases 1, 2 and 3.

In addition, as stated in the 16-bus test system, when we have DGs capable of generating active power or both active and reactive power, we have better results. Comparing Case 4 to Case 1, there is a reduction of 21.23% in total costs. The major difference is now in active and reactive power losses. There is approximately 98.76% and 97.99% reduction in power losses, respectively. This is a big positive impact in the system that is translated into almost linear voltage profile as we can see in Figure 5.18. In this distribution system, that is larger than the 16-bus test system, the effects are more visible.

Table 5.4 – Results of Relevant Variables for Different Cases.

Cases	Total Cost [€/h]	Total Active Power Losses [MW]	Total Reactive Power Losses [Mvar]	Total installed DG size [MVA]	Computation time [s]
1	228.1816	0.1865	0.0999	0	-
2	226.9463	0.1249	0.0825	0	24.423398
3	226.9593	0.1256	0.0830	0	27.102581
4	179.7385	0.0023	0.0020	23	32.926209
5	180.0747	0.0443	0.0333	17	39.599780
6	226.1954	0.0876	0.0672	15	34.074488

Table 5.5 - Branches Opened and DG Location in 33-bus Distribution System.

Cases	Opened branches	DG Bus Location
1	21-8; 9-15; 12-22;18-33;25-29	-
2	7-8; 9-10; 14-15; 32-33;25-29	-
3	7-8; 10-11; 14-15; 32-33; 25-29	-
4	7-8; 11-12; 15-16; 21-22; 28-29	4; 9; 16; 17; 20; 22; 23; 24; 26; 30; 31; 32
5	6-7; 11-12; 14-15; 26-27; 32-33	5; 8; 12; 13; 14; 17; 23; 25; 28; 31; 33
6	7-8; 8-9; 14-15; 28-29; 32-33	5; 6; 13; 15; 22; 24; 30; 32

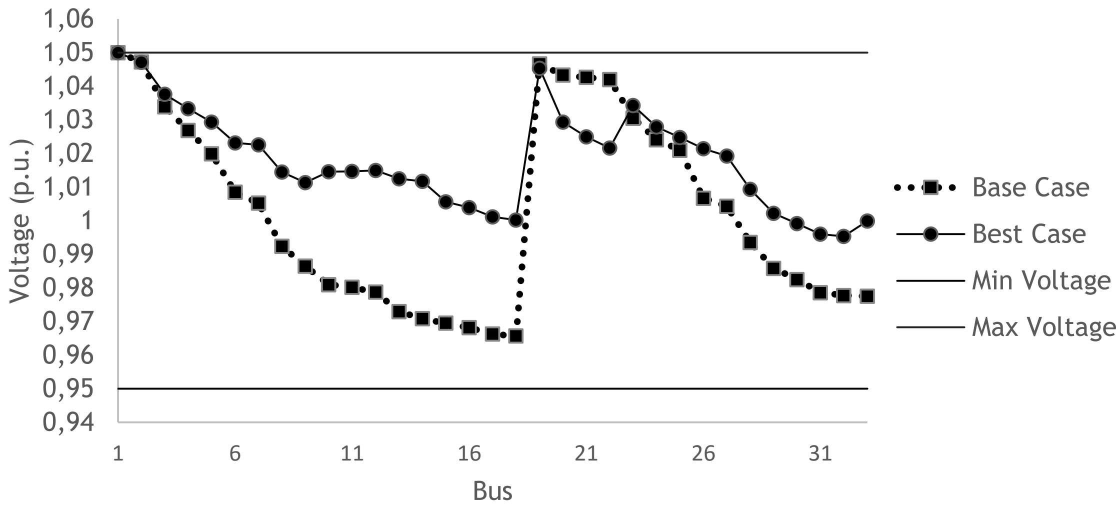

Figure 5.16 - Voltage comparison between Case 1 and Case 2.

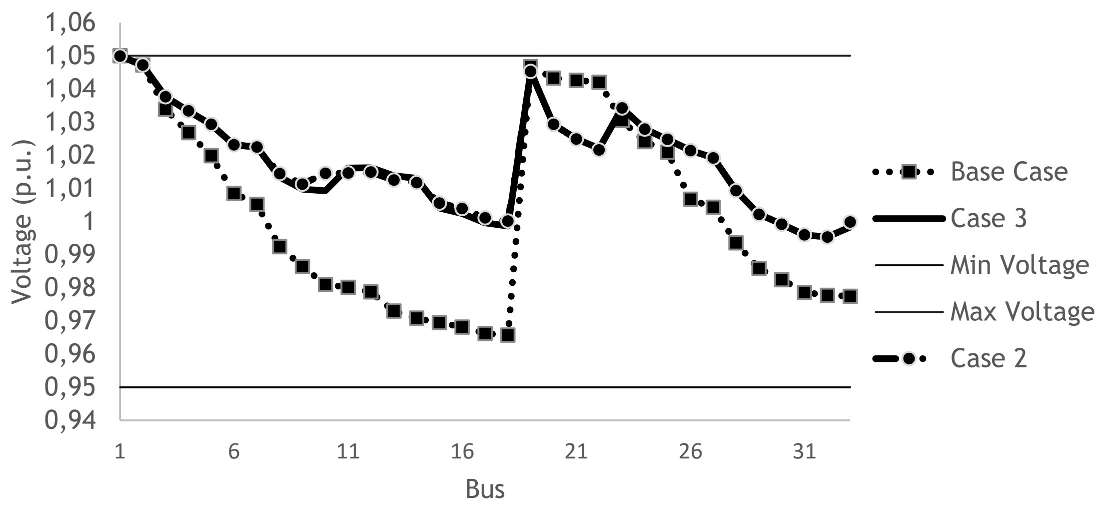

Figure 5.17 - Voltage comparison between base Case 1, Case 2 and Case 3.

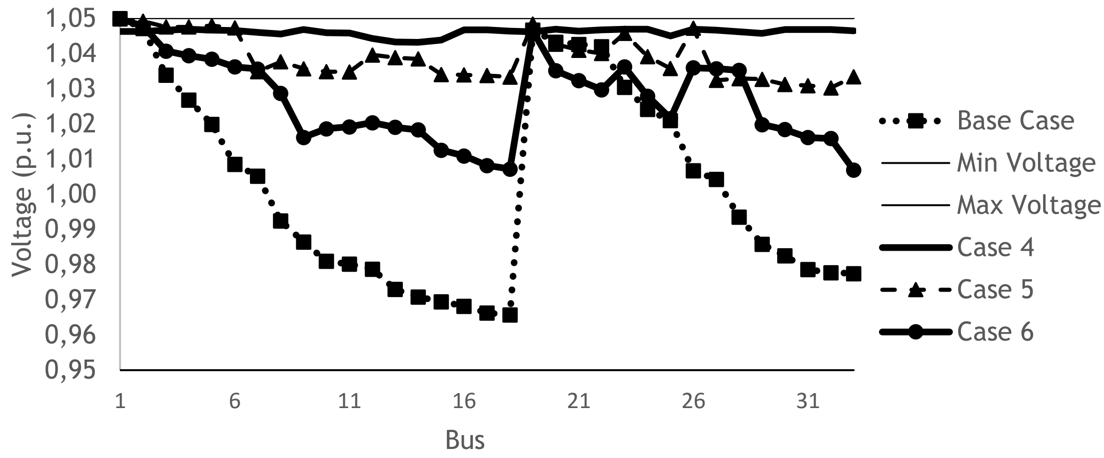

Figure 5.18 - Voltage comparison between Case 1 and Case 4, 5, 6.

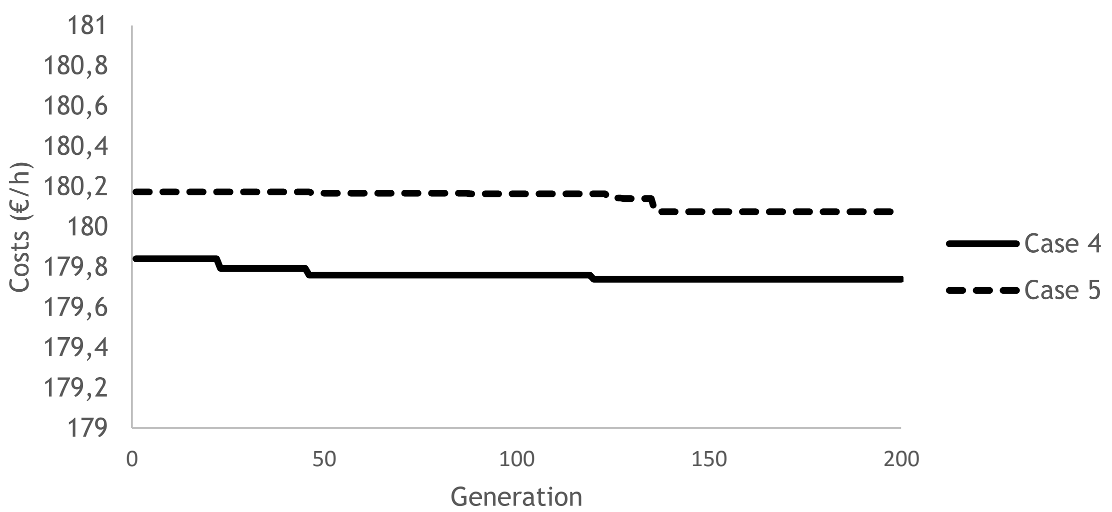

Figure 5.19 - Convergence process in Case 4 and 5.

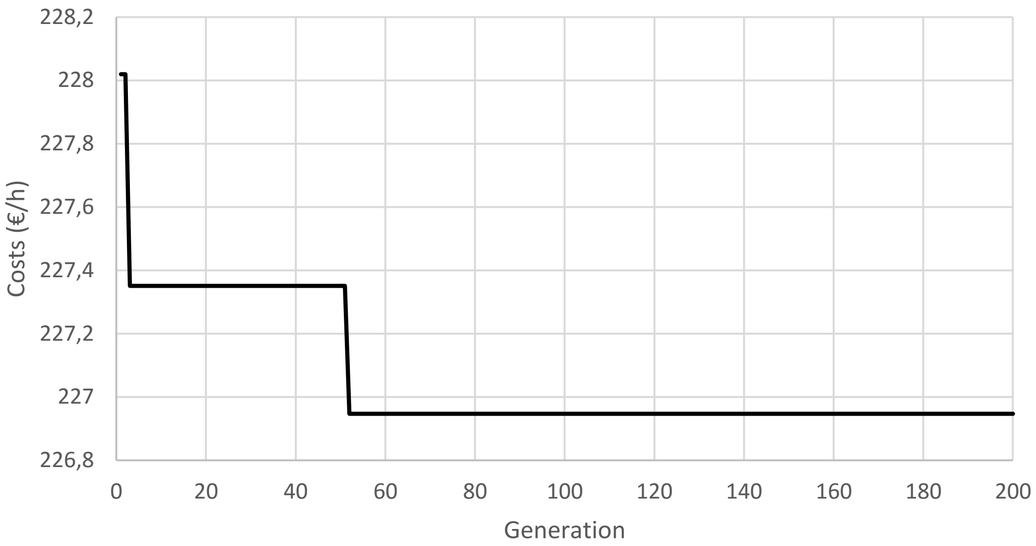

Figure 5.20 – Convergence process in Case 6

The voltages are with a linear profile when DGs are placed in the system. The effects of having DGs capable of producing only active or reactive power are also seen in the Figure 5.18. With active power only DGs, we can have also a better voltage profile, not so linear as in Case 4 but significantly better than the base case. Deploying reactive power only DGs also has impact in systems losses, and voltage profiles. In Case 5, the reduction in total costs is 20.65% compared with Case 2 and 21.08% when compared with Case 1. Compared with Case 2, active and reactive power losses are reduced by 76.22% and 66.68% respectively.

As in Case 6, there is no big impact in total costs, only 0.87% when compared with Case 1 but, there is a huge difference in terms of losses. Compared with Case 1, the active and reactive power losses are reduced by 53.04% and 32.69%, respectively. Although the costs are slightly increased, the benefits of having DGs with this technology are evident with the reduction of losses and improvement in voltage profile. However, as mentioned earlier, this can be dependent on the convergence process of the GA. In Cases 4 and 5, as illustrated in Figure 5.19, in the first generation, we are getting better results in terms of costs than in Case 1. Placement and sizing of DGs may not be optimal because of the solution method. However, there are small differences from generation to generation, probably indicating the closeness of the solution to the optimal one.

Figure 5.20 shows the convergence process of Case 6 and, in first generation, there is a worse scenario than base case. This seems to perpetuate throughout the simulation leading to worse costs but with better voltage profile and loss reduction.

In Case 4, the first best generation is with a value of 179.8402 €/h, with a difference of 0,06% compared with that of the best solution (179.7385€/h). And, this is the same for Case 5, in which the difference of the first generation to the last generation is about 0,05%. We can observe the convergence process in Case 2 and the difference in terms of costs for the first and the last generation is about 0,47%. The algorithm probably reached the optimal solution in the generation 52, and it is still the same until the last generation.

The convergence time is 24.423398 seconds with a population of 200 individuals. It is worth mentioning here that each simulation can lead to a different solution but with small differences. This may be mainly because switching off one branch or another may not lead significant difference in costs (about 0.12%).

The configuration outcome of Case2 is shown in Figure 5.21. Figure 5.22 shows the DG placement and size in Case 4, Case 5 and Case 6. In Figure 5.23, there are the configuration and DG placement for Case 4. It seems that there is no connection between Cases 4, 5 and 6 with respect to locating the critical buses to install DG. We can make a connection between Cases 4 and 5 as well as Cases 4 and 6. Recall that Case 4 considers DGs with active and reactive power generation capability while active power only and reactive power only DGs are considered in Cases 5 and 6, respectively Having this in mind, Case 4 and Case 5 seem to have common optimal DG locations including buses 17, 23 and 31. Case 4 and Case 6 also have common "optimal" DG locations such as buses 22, 24, 30 and 32. When we look at the demand and at the total installed size of DG, there seems to be a lot of discrepancies among the different cases.

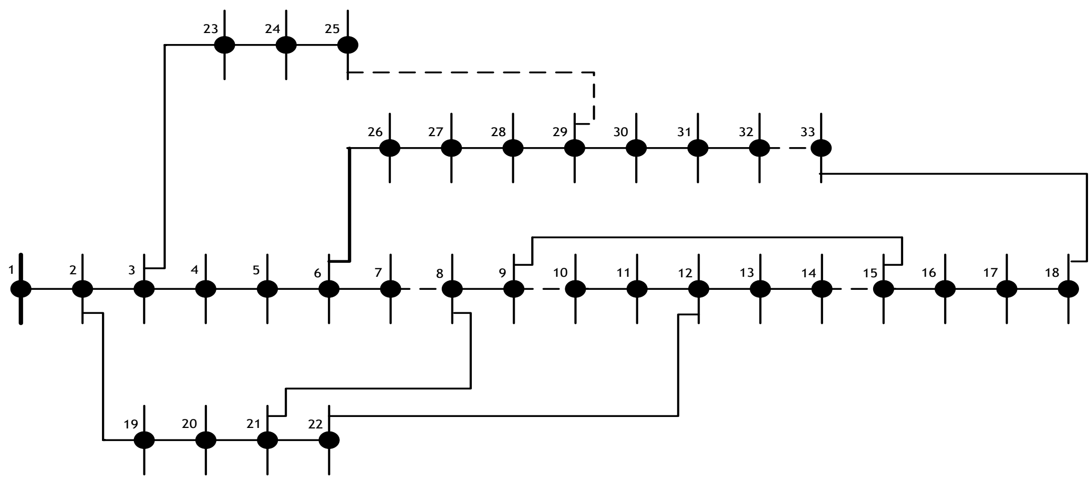

Figure 5.21 - Configuration in Case 2.

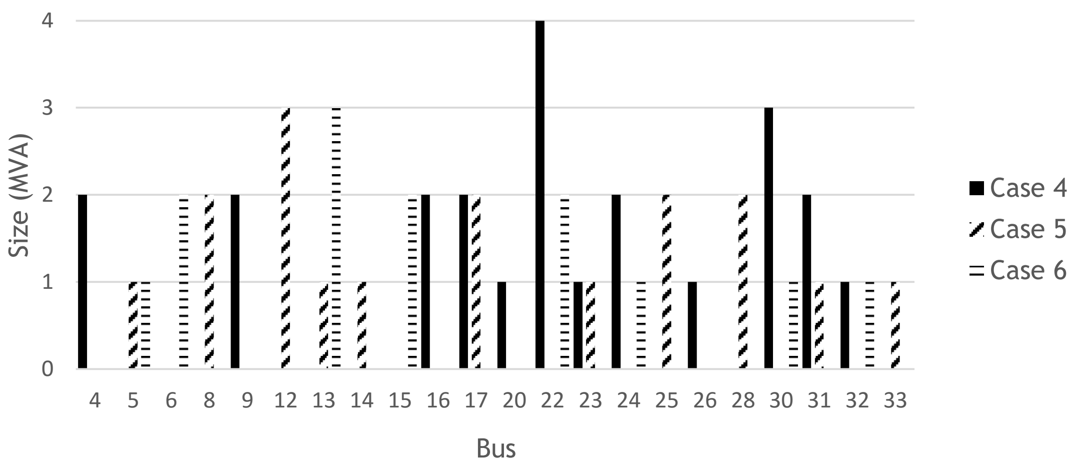

Figure 5.22 - DG size and placement in Cases 4, 5 and 6.

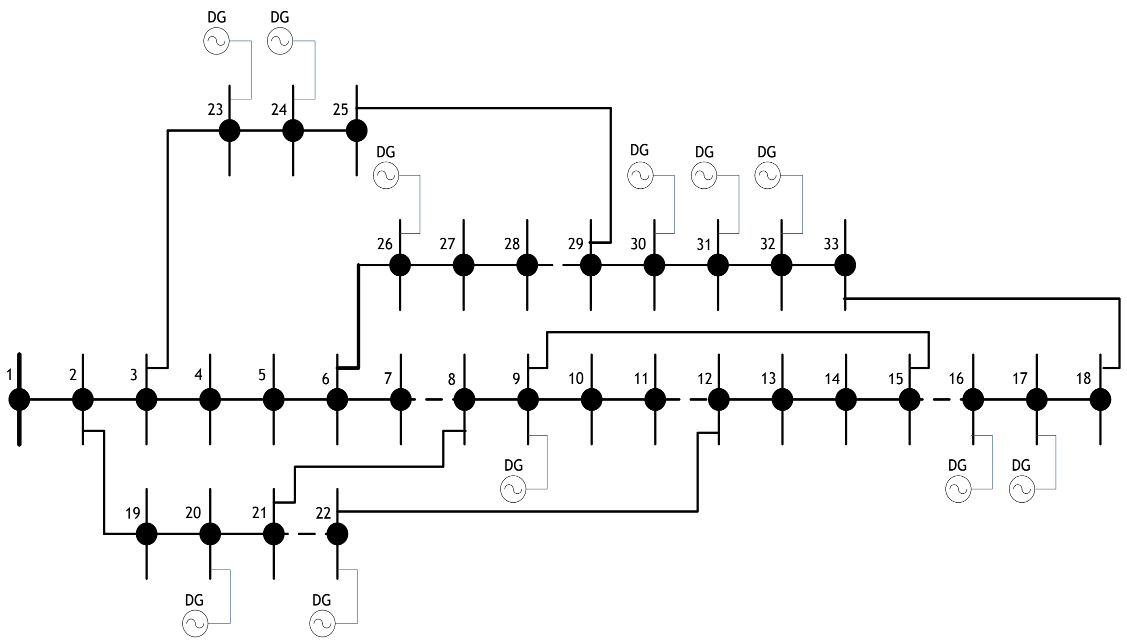

Figure 5.23 - Configuration and DG placement Case 4

5.3 – Summary

Numerical results in GA showed that having reconfiguration can lead to a better voltage profile, reduced costs and losses in the operational stage. But taking in consideration solely costs or total losses cannot lead us to the optimal performance because, sometimes, reaching the minimum costs with a certain configuration may not agree with lowering the total losses in the system. Hence, it is necessary to have in consideration total losses and total costs, making the operational scenario as a weighted sum of these two measures, or handling it as a multi-objective optimization. This is because, when we have a generator more expensive than the others in the system, the reconfiguration with objective to minimize costs will seek that this generator feeds the lowest possible demand in order to reduce the costs, making that the others generators feed a larger number of demand, becoming a larger radial system to feed, increasing the losses. When we only seek to minimize the losses with a generator more expensive than the others in the system, we will get the best configuration possible, with the best voltage profile but, the more expensive generator will participate more in the system, feeding more load, the costs of operation will increase. This may however be case dependent.

The reconfiguration of the 33-bus network system leads to a better voltage profile in almost all the nodes. But as this is a GA, we cannot be sure that we have the optimal objective function value

Lower costs and lower losses in the new configuration of the 33-bus network system are evident. The comparison between minimization of losses and minimization of costs for reconfiguration purpose do not show significant differences. However, this may also be case dependent.

A MILP model was developed that involves joint optimization of placement and sizing of RES-based DGs and ESSs in coordination with optimal network switching. Numerical results showed the capability of ESSs integration in dramatically increasing the level and optimal exploitation of renewable DGs. According to the simulation results, the simultaneous integration of DGs and ESSs resulted in an overall cost and average losses reduction. The optimal network reconfiguration, DG and ESS installations substantially contributed to voltage stability.

Chapter 6

Conclusions and Future Works

6.1 – Conclusions

This thesis work has developed a stochastic MILP optimization model that jointly optimizes RES integration with ESSs and switching/reinforcement of the distribution network taking in consideration the variable and uncertain nature of RES based-DGs. The formulation of such a problem in a MILP form means that exact and efficient solution techniques commercially available can be used, and optimality is guaranteed within a finite simulation time. In addition, a series of related problems such as network reconfiguration as well as DG allocation and sizing are formulated in such a way that GA can be employed. The thesis present an extensive qualitative and quantitative analysis made in both approaches. In the case of GA-based model, one of the goals of the analysis has been to analyse the influence of integrating DGs and reconfiguration in the distribution network systems with a single operation scenario. The MILP based analysis has been carried out considering a detailed representation of several operational situations (introduced as a result of the stochastic nature of RESs and demand) and different low frequency uncertain parameters such as emission prices. Moreover, the impacts of network switching/expansion as well as deploying distributed ESSs on the DG integration levels have been investigated.

Simulation results from GA-based analysis have showed the significant benefits in lowering costs, reducing total losses and improving voltage profiles in the system. Even if the analysis made in this thesis involves only one operational scenario, the benefits are very evident. But numerical results show that the integration in the system of DG have very significant impact in total losses. In the 33-bus test system, almost 99% reduction of active power losses and 98% of reactive power losses are achieved by the integration of DGs with reactive power support capabilities. The impact on the overall voltage profile in the system is also dramatic, leading to almost linear profile throughout the system. The integration of DGs with a capability to produce and consume reactive power is a scenario where improvement in voltage is significant.

But the cost function of DGs is generic and the intention of this analysis is to understand the positive impacts in coordinating a distribution system with DG and reconfiguration.

The simulation results also show that considering DGs with reactive power support capability leads to a higher integration of such DG technologies. In addition, the results obtained from cases that consider only reconfiguration of the system have indicated a better voltage profile, and a reduction in total active and reactive power losses of 61.59% and 17.38%, respectively. Total costs of the system are reduced by 0.54% when compared to the base case. This shows the impacts the reconfiguration of the distribution system especially in loss reduction, and improving voltage profile.

All these analyses point to the need for an exact planning tool of DGs along with ESSs, and distribution reconfiguration and/or expansion. In real-life, such a problem is a very complex, nonlinear, nonconvex and combinatorial. However, this thesis has developed a comprehensive planning tool that is a tractable optimization model considering relevant stochastic parameters, major cost drivers and factors in a multi-stage and multi-scenario planning framework. In addition, the thesis also contributes to an extensive analysis made on a medium scale network. The joint optimization model is formulated as a stochastic programming. And, in the stochastic formulation, we need to have in mind that DGs are variable and uncertain. The best way to minimize the impacts of DGs is the place and size of ESSs. In addition, taking into consideration the difficulty of GA to provide an exact solution, sometimes "wandering" near the optimal solution or getting stuck in local optima, a new MILP formulation has been proposed that handles multiple objective functions, taking into consideration the costs not only for the operation, but also the investment in DGs, investment in the network, costs of emission and costs of unserved power. The numerical results from S-MILP have showed the capability of ESSs integration in dramatically increasing the level and optimal exploitation of renewable DGs. According to the simulation results, the simultaneous integration of DGs and ESSs resulted in an overall cost and average losses reduction of 41% and 84%, respectively. The optimal network reconfiguration, DG and ESS installations (jointly or separately) substantially contributed to voltage stability. In the particular case study, the impact of network switching on RES power integration was not significant. However, it should be noted that this can be case-dependent.

6.2 – Future Works

The analysis in the GA-based model can be further extended by considering different operational situations (instead of one), ESSs, different cost drivers such as emission costs, etc. The issues accounted for in the MILP model can be transferred to the GA-based model and the results obtained by both can be compared. Relevant conclusions can be drawn from such comparative results.

6.3 – Works Resulting from this Thesis

The paper prepared based on this thesis can be found in Annex and was accepted and presented at the 13th International Conference on the European Energy Market — EEM 2016 (technically co-sponsored by IEEE), Porto, 9 June 2016.

M. R. Cruz, D. Z. Fitiwi, and S. F. Santos, “Influence of Distributed Storage Systems and Network Switching/Reinforcement on RES-based DG Integration Level”, in European Energy Market (EEM), 13th International Conference on, 2016, pp. 1-5.

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ANNEX

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Influence of Distributed Storage Systems and Network Switching/Reinforcement on RES-based DG Integration Level

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***Abstract*—Nowadays, there is a global consensus that integrating renewable energy sources (RES) is highly needed to meet an increasing demand for electricity and reduce the overall carbon footprint of power production. Framed in this context, the coordination of RES integration with distributed energy storage systems (DESS), along with the network's switching capability and/or network reinforcement, is expected to significantly improve system flexibility, thereby increasing chances of accommodating large-scale RES power. This paper presents an innovative method to quantify the impacts of network switching and/or reinforcement as well as installing DESSs on the level of renewable power integrated in the system. To carry out this analysis, a dynamic and multi-objective stochastic mixed integer linear programming (S-MILP) model is developed, which jointly takes into account the optimal RES-based DGs and DESS integration in coordination with distribution network reinforcement and/or switching. A standard distribution network system is used as a case study. Numerical results show the capability of DESSs integration in dramatically increasing the level of renewable DGs integrated in the system. Although case-dependent, the impact of network switching on RES power integration is not significant.**

***Index Terms*—Distributed energy storage systems, distributed generation, network reinforcement, network switching, RESs.**

I. NOMENCLATURE

A. *Sets/Indices*

i/Ω^i	Index/set of buses
$g/\Omega^g/\Omega^{DG}$	Index/set of generators/DGs
k/Ω^k	Index/set of branches
s/Ω^s	Index/set of yearly scenarios
t/Ω^t	Index/set of planning stages
w/Ω^w	Index/set of hourly snapshots
$\varsigma/\Omega^\varsigma$	Index/set of substations

B. *Parameters*

$ER_g^N, ER_g^E, ER_\varsigma^{SS}$	Emission rates of new and existing DGs, and energy purchased, respectively (tCO₂e/MWh)
$IC_{g,i}, IC_k, IC_{es,i}$	Investment cost of DG, line and energy storage, respectively (M€)
$LT_g, LT_k, LT_{tr}, LT_{es}$	Lifetimes of DG, distribution line, transformer and energy storage system, respectively (years)
MC_{es}, MC_{tr}	Maintenance cost of storage/trafo per year (M€)
MC_g^N, MC_g^E	Maintenance costs of new and existing DGs (M€/yr)
MC_k^N, MC_k^E	Maintenance cost of new and existing line (M€/yr)
$OC_{g,i,s,w,t}^N, OC_{g,i,s,w,t}^E$	Operation cost of unit energy production by new and existing DGs (€/MWh)
$\lambda_{s,w,t}^{CO_2e}$	Price of emissions (€/tons of CO_2 equivalent)
$\lambda_{s,w,t}^{\varsigma}$	Price of electricity purchased (€/MWh)
ρ_s, π_w	Probability of yearly scenario *s* and weight (in hours) of hourly snapshot group *w*
$\upsilon_{s,w,t}$	Penalty for unserved power (€/MW)
$\eta_{ch,es}$	Charging efficiency (%)
μ_{es}	Scaling factor (%)

C. *Variables*

$\delta_{i,s,w,t}$	Unserved power at node *i* (MW)
$D_{s,w,t}^i$	Active power demand at node *i* (MW)
$P_{g,i,s,w,t}^N, P_{g,i,s,w,t}^E$	Power produced by new and existing DGs (MW)
$P_{\varsigma,s,w,t}^{SS}$	Active power imported from grid (MW)
$u_{g,i,t}, u_{k,t}$	Utilization variables of existing DG and lines
$x_{g,i,t}, x_{es,i,t}, x_{k,t}$	Investment variables for DG, storage systems and distribution lines, respectively
$\varphi_{k,s,w,t}$	Losses associated to each feeder (MW)
$E_{es,i,s,w,t}$	Reservoir level of ESS (MWh)
$I_{es,i,s,w,t}^{dch}, I_{es,i,s,w,t}^{ch}$	Discharging/charging indicator variables
$P_{es,i,s,w,t}^{dch}, P_{es,i,s,w,t}^{ch}$	Discharged/charged power (MW)
$x_{tr,ss,t}$	Transformer investment variable

D. *Functions (all units are in M€)*

EC_t^{SS}	Expected cost of energy purchased from upstream
$ENSC_t$	Expected cost of unserved power
$EmiC_t^{DG}$	Expected emission cost of DG power production
$EmiC_t^N, EmiC_t^E$	Expected emission cost of power production using new and existing DGs, respectively
$EmiC_t^{SS}$	Expected emission cost of purchased power
$InvC_t^{DNS}, MntC_t^{DNS}$	NPV investment/maintenance cost of DNS components
$InvC_t^{DG}, MntC_t^{DG}, EC_t^{DG}$	NPV investment/maintenance/expected energy cost of DGs, respectively
$InvC_t^{LN}, MntC_t^{LN}$	NPV investment/maintenance cost of a line
$InvC_t^{ES}, MntC_t^{ES}$	NPV investment/maintenance cost of ESS

II. INTRODUCTION

A. *Motivation and Aims*

The issue of integrating renewable distributed generations (DGs) in power distributions systems is becoming very critical because of technical, economic and environmental reasons. Nowadays, there is a global consensus that integrating renewable energy sources—RESs, is highly needed to meet an increasing demand for electricity and reduce the overall carbon footprint of energy production. However, large-scale integration of RES-based DGs often poses a number of technical challenges in the system from the stability, reliability and power quality perspective. This is because integrating RESs introduces significant operational variability and uncertainty to the distribution system, making operation, planning and control rather complicated. Hence, such a high level integration effort is likely to be supported by certain smart-grid technologies and concepts that have the capability to enhance the flexibility of the entire distribution systems. Framed in this context, the integration of distributed energy storage systems (DESSs) jointly with DGs, along with the network's switching capability and/or network reinforcement, significantly improves the flexibility of the system, thereby increasing chances of accommodating large-scale RES power.

This paper presents a method to quantify the influences of simultaneous consideration of investments in DESSs as well as network switching and/or reinforcement on the level of renewable power integrated in the system. To carry out this analysis, a stochastic mixed integer linear programming (S-MILP) model is developed which takes account of distribution network reinforcement and/or switching in coordination with investments in RES-based DGs and DESS technologies.

B. Literature Review

RESs make a crucial part of the solution for environmental sustainability; hence, they will play an important role in power systems [1]. The integration of RESs should, in principle, reduce the risk of fuel price volatility and geopolitical pressures and ensure that these do not pose a significant impact on the overall public welfare [2], [3]. However, large-scale penetration of RESs will necessarily involve a process of adapting and changing the existing infrastructure because of their intrinsic characteristics, such as intermittency and variability. The growing need for intermittent RESs, in conjunction with the electrical mix changes in the long-term, will probably affect the distribution and transmission systems. In this context, a change in power generation options, resulting from a high contribution of RESs, may require network grid updates. Regulatory agencies are heavily committed to increase RES integration, not only due to environmental but also technical and economic reasons [4].

The main challenge with most of RESs is their inherent variability and uncertainty, making operation, control and planning very complicated. DG penetration increases the variation of voltage and current in the network. Hence, increasing DG penetration may have a negative or positive impact depending on various factors such as the size of the system and the loads type, requiring modeling and simulations to assess its impact [5]. If not properly planned, this may lead to an uncertain increase in the feeders' power flows, resulting in network congestion and increased losses in the network. However, the integration of DESS with RESs have become one of the most viable solutions to facilitate the increased penetration of DG resources [4], [6]. Energy storage systems level the mismatch between renewable power generation and demand [6]. This is because these devices store energy during periods of low electricity demand (price) or high RES power production, and the release it during periods of peak demand and low RES production [7]. Therefore, in addition to their technical support to the system, ESSs bring substantial benefits for end-users and DG owners through reliability and power quality improvement as well as cost reduction [8]. Besides, ESSs are being developed and applied in power grids to cope with a number of issues such as smoothing the energy output from RESs, improving the stability of the electrical system, etc. [9]. ESSs also increase savings during peak hours and minimize the impact of intermittent generation sources, leading to a more efficient management of the integrated system.

Electrical distribution systems are interconnected by switches but predominantly operated radially. These switches are often used for emergency purposes such as to evade load curtailment during fault cases. However, the system can be reconfigured to find the best topology that minimizes power losses in the system and improve operational performance, in general [10], [11]. Ref. [12] discusses distribution network reconfiguration for minimizing losses in the presence of variable energy sources. Authors in [13] have investigated the impact of load variability on network reconfiguration outcome. In [14], [15], authors have studied distribution system reconfiguration with the aim of reducing energy losses under normal conditions. As the network topology can be adjusted by the change of switches state in the lines (normally opened/closed), the optimal management of the entire system has to find the optimal network configuration, allowing greater network flexibility [16], which may in turn allow large-scale RES integration. The work in [17] considers dynamic reconfiguration with a possibility of remotely controlling switches in an active and centralized management framework, with the aim of removing network congestion in real time.

The present work presents a qualitative and quantitative analysis regarding the impact of joint integration ESSs, network switching (reconfiguration) and reinforcement on the level of DG integration (particularly, focusing on RESs). For carrying out this analysis, a multi-objective S-MILP model is developed considering the operational variability and uncertainty of variable power resources.

C. Contributions and Paper Organization

The main contributions of this work are twofold:

- A multi-stage and stochastic optimization model, which considers simultaneous integration of DESSs and variable generation sources as well as network switching/investments;
- A thorough analysis related to the influence of network flexibility (switching capability, investments) and/or DESS installations made in coordination with investments in variable generation sources on the RES integration level, system cost and losses.

The rest is organized as follows. Section III presents a brief description of the developed mathematical model. Numerical results are discussed in Section IV. The final section concludes this paper.

III. Model Formulation

The dynamic and multi-objective S-MILP optimization model developed here is described as follows.

A. Objective Function

The problem is formulated as a multi-objective stochastic MILP with an objective of overall cost minimization as in (1). The objective function in (1) is composed of Net Present Value (NPV) of five cost terms each weighted by a certain relevance factor $\gamma_j; \forall j \in \{1,2,\ldots,5\}$.

The first term in (1), $TInvC$, represents the total investment costs under the assumption of perpetual planning horizon [18]. In other words, "the investment cost is amortized in annual installments throughout the lifetime of the installed component", as is done in [19].

Here, the total investment cost is the sum of investment costs of DGs, distribution network system (DNS) components (feeders and transformers) and ESSs, as in (2). And, this cost is computed as in (7)-(9). The second term, TMC, in (1) denotes the total maintenance costs, which is given by the sum of maintenance costs of new and existing DGs as well as that of DNS components and ESSs at each stage and the corresponding costs incurred after the last planning stage, as in (3). Note that the latter depend on the maintenance costs of the last planning stage according a perpetual planning horizon. These maintenance costs are computed according to Eqs. (10)-(12).

The third term TEC in (1) refers to the total cost of energy in the system, which is the sum of the cost of power produced by new and existing DGs, supplied by ESSs and purchased from upstream at each stage as in (4). Eq. (4) also includes the total energy costs incurred after the last planning stage under the assumption of perpetual planning horizon. These depend on the energy costs of the last planning stage. The detailed mathematical expressions for computing the cost of DG power produced and ESS power supplied as well as that of purchased power are given in (13), (14) and (15), respectively.

The fourth term $TENSC$ represents the total cost of unserved power in the system, given as in (5). And, this is computed using Eq. (16). The last term $TEmiC$ gathers the total emission costs in the system, given by the sum of emission costs for the existing and new DGs (17)-(19) as well that of purchased power (20).

$$Minimize\ TC = \gamma_1 * TInvC + \gamma_2 * TMC + \gamma_3 * TEC + \gamma_4 * TENSC + \gamma_5 * TEmiC \tag{1}$$

$$TInvC = \underbrace{\sum_{t\epsilon\Omega^t}(1+r)^{-t}(InvC_t^{DG} + InvC_t^{DNS} + InvC_t^{ES})/r}_{NPV\ of\ investment\ cost} \tag{2}$$

$$TMC = \underbrace{\sum_{t\epsilon\Omega^t}(1+r)^{-t}\ (MntC_t^{DG} + MntC_t^{DNS} + MntC_t^{ES})}_{NPV\ of\ maintenance\ costs} + \underbrace{(1+r)^{-T}(MntC_T^{DG} + MntC_T^{DNS} + MntC_T^{ES})/r}_{NPV\ maintenance\ costs\ incured\ after\ stage\ T} \tag{3}$$

$$TEC = \underbrace{\sum_{t\epsilon\Omega^t}(1+r)^{-t}\ (EC_t^{DG} + EC_t^{SS} + EC_t^{ES})}_{NPV\ of\ operation\ costs} + \underbrace{(1+r)^{-T}(EC_T^{DG} + EC_T^{SS} + EC_T^{ES})/r}_{NPV\ operation\ costs\ incured\ after\ stage\ T} \tag{4}$$

$$TENSC = \underbrace{\sum_{t\epsilon\Omega^t}(1+r)^{-t}\ ENSC_t}_{NPV\ of\ reliability\ costs} + \underbrace{(1+r)^{-T}ENSC_T/r}_{NPV\ reliability\ costs\ incured\ after\ stage\ T} \tag{5}$$

$$TEmiC = \underbrace{\sum_{t\epsilon\Omega^t}(1+r)^{-t}\ (EmiC_t^{DG} + EmiC_t^{SS})}_{NPV\ emission\ costs} + \underbrace{(1+r)^{-T}(EmiC_T^{DG} + EmiC_T^{SS})/r}_{NPV\ emission\ costs\ incured\ after\ stage\ T} \tag{6}$$

$$InvC_t^{DG} = \sum_{g\epsilon\Omega^g}\sum_{i\epsilon\Omega^i}\frac{r(1+r)^{LT_g}}{(1+r)^{LT_g-1}}IC_{g,i}(x_{g,i,t} - x_{g,i,t-1})\ ;where\ x_{g,i,0} = 0 \tag{7}$$

$$InvC_t^{DNS} = \sum_{k\epsilon\Omega^\ell}\frac{r(1+r)^{LT_k}}{(1+r)^{LT_k-1}}IC_k(x_{k,t} - x_{k,t-1}) + \sum_{ss\epsilon\Omega^{ss}}\sum_{tr\epsilon\Omega^{tr}}\frac{i(1+i)^{LT_{tr}}}{(1+i)^{LT_{tr}-1}}IC_{tr}\left(x_{tr,ss,t} - x_{tr,ss,t-1}\right);\ where\ x_{k,0} = 0\ and\ x_{tr,ss,0=0} \tag{8}$$

$$InvC_t^{ES} = \sum_{c\epsilon\Omega^c}\sum_{i\epsilon\Omega^i}\frac{r(1+r)^{LT_{ess}}}{(1+r)^{LT_{es}-1}}IC_c(x_{es,i,t} - x_{es,i,t-1})\ ;where\ x_{es,i,0} = 0 \tag{9}$$

$$MntC_t^{DG} = \sum_{g\epsilon\Omega^g}\sum_{i\epsilon\Omega^i}MC_g^N\, x_{g,i,t} + \sum_{g\epsilon\Omega^g}\sum_{i\epsilon\Omega^i}MC_g^E\, u_{g,i,t} \tag{10}$$

$$MntC_t^{DNS} = \sum_{k\epsilon\Omega^{e\ell}}MC_k^E\, u_{k,t} + \sum_{k\epsilon\Omega^{n\ell}}MC_k^N\, x_{k,t} + \sum_{tr\epsilon\Omega^{E\_tr}}MC_{tr}^E\, u_{tr,ss,t} + \sum_{tr\epsilon\Omega^{N\_tr}}MC_k^N\, x_{tr,ss,t} \tag{11}$$

$$MntC_t^{ES} = \sum_{c\epsilon\Omega^c}\sum_{i\epsilon\Omega^i}MC_{es}x_{es,i,t} \tag{12}$$

$$EC_t^{DG} = \sum_{s\epsilon\Omega^s}\rho_s\sum_{w\epsilon\Omega^w}\pi_w\sum_{g\epsilon\Omega^g}\sum_{i\epsilon\Omega^i}(OC_{g,i,s,w,t}^N P_{g,i,s,w,t}^N + OC_{g,i,s,w,t}^E\, P_{g,i,s,w,t}^E) \tag{13}$$

$$EC_t^{ES} = \sum_{s\epsilon\Omega^s}\rho_s\sum_{w\epsilon\Omega^w}\pi_w\sum_{es\in\Omega^{es}}\lambda_{s,w,t}^{es}P_{es,i,s,w,t}^{dch} \tag{14}$$

$$EC_t^{SS} = \sum_{s\epsilon\Omega^s}\rho_s\sum_{w\epsilon\Omega^w}\pi_w\sum_{\varsigma\in\Omega^\varsigma}\lambda_{s,w,t}^{\varsigma}P_{\varsigma,s,w,t}^{SS} \tag{15}$$

$$ENSC_t = \sum_{s\epsilon\Omega^s}\rho_s\sum_{w\epsilon\Omega^w}\sum_{i\epsilon\Omega^i}\pi_w\upsilon_{s,w,t}\delta_{i,s,w,t} \tag{16}$$

$$EmiC_t^{DG} = EmiC_t^N + EmiC_t^E \tag{17}$$

$$EmiC_t^N = \sum_{s\epsilon\Omega^s}\rho_s\sum_{w\epsilon\Omega^w}\pi_w\sum_{g\epsilon\Omega^g}\sum_{i\epsilon\Omega^i}\lambda_{s,w,t}^{CO_2e}ER_g^N P_{g,i,s,w,t}^N \tag{18}$$

$$EmiC_t^E = \sum_{s\epsilon\Omega^s}\rho_s\sum_{w\epsilon\Omega^w}\pi_w\sum_{g\epsilon\Omega^g}\sum_{i\epsilon\Omega^i}\lambda_{s,w,t}^{CO_2e}ER_g^E P_{g,i,s,w,t}^E \tag{19}$$

$$EmiC_t^{SS} = \sum_{s\epsilon\Omega^s}\rho_s\sum_{w\epsilon\Omega^w}\pi_w\sum_{\varsigma\epsilon\Omega^\varsigma}\sum_{i\epsilon\Omega^i}\lambda_{s,w,t}^{CO_2e}ER_\varsigma^{SS}P_{\varsigma,s,w,t}^{SS} \tag{20}$$

B. Constraints

The active power balance at each node is enforced by:

$$\sum_{g\epsilon\Omega^{DG}}\left(P_{g,i,s,w,t}^E + P_{g,i,s,w,t}^N\right) + \sum_{es\epsilon\Omega^{es}}\left(P_{es,i,s,w,t}^{dch} - P_{es,i,s,w,t}^{ch}\right) + P_{\varsigma,s,w,t}^{SS} + \sum_{in,k\epsilon i}P_{k,s,w,t} - \sum_{out,k\epsilon i}P_{k,s,w,t} + \delta_{i,s,w,t} = \sum_{in,k\epsilon i}0.5\varphi_{k,s,w,t} + \sum_{out,k\epsilon i}0.5\varphi_{k,s,w,t} + D_{s,w,t}^i\ ;\ \forall\varsigma, \forall\varsigma\epsilon i \tag{21}$$

Eq. (21) denotes that the sum of all incoming flows should be equal to the sum of all outgoing flows at each node. Note that losses in every feeder are considered as "virtual loads" which are equally distributed between the nodes connecting the feeder. Note that losses are a quadratic function of flows (not shown here). Hence, they are linearized using first order approximation, as in [19].

For the sake of simplicity, a generic ESS is employed here. And, this is modeled by the set of constraints in (22)-(28). Eqs. (22) and (23) represent the bounds of power capacity of the ESS while being charged and discharged, respectively. Inequality (24) prevents simultaneous charging and discharging operation of ESS at the same operational time w. The amount of stored energy within the ESS reservoir at a given operational time w as a function of the energy stored until $w-1$ is given by (25). The maximum and minimum levels of storages in the operational time w are also considered through inequality (26). Eq. (27) shows the initial level of stored energy in the ESS as a function of its maximum reservoir capacity. In a multi-stage planning approach, Eq. (28) ensures that the initial level of energy in the ESS at a given year is equal to the final level of energy in the ESS in the preceding year. Here, η_{es}^{dch} is assumed to be $1/\eta_{es}^{ch}$.

$$0 \le P_{es,i,s,w,t}^{ch} \le I_{es,i,s,w,t}^{ch}x_{es,i,t}P_{es,i}^{ch,max} \tag{22}$$

$$0 \le P_{es,i,s,w,t}^{dch} \le I_{es,i,s,w,t}^{ch}x_{es,i,t}P_{es,i}^{ch,max} \tag{23}$$

$$I_{es,i,s,w,t}^{ch} + I_{es,i,s,w,t}^{dch} \le 1 \tag{24}$$

$$E_{es,i,s,w,t} = E_{es,i,s,w-1,t} + \eta_{ch,es}P_{es,i,s,w,t}^{ch} - \eta_{dch,es}P_{es,i,s,w,t}^{dch} \tag{25}$$

$$E_{es,i}^{min}x_{es,i,t} \le E_{es,i,s,w,t} \le x_{es,i,t}E_{es,i}^{max} \tag{26}$$

$$E_{es,i,s,w_0,T1} = \mu_{es}x_{es,i,T1}E_{es,i}^{max} \tag{27}$$

$$E_{es,i,s,w_1,t+1} = E_{es,i,s,W,t} \tag{28}$$

Notice that inequalities (22) and (23) involve products of charging/discharging indicator variables and investment variable. In order to linearize this, new continuous positive variables $z_{es,i,s,w,t}^{ch}$, and $z_{es,i,s,w,t}^{dch}$, which replaces the bilinear products in each constraint, is introduced such that the set of linear constraints in (29) and (30) hold. For instance, the product $I_{es,i,s,w,t}^{dch}x_{es,i,t}$ is replaced by the positive variable $z_{es,i,s,w,t}^{dch}$. Then, the bilinear product is decoupled by introducing the set of constraints in (29) [20].

$$z_{es,i,s,w,t}^{dch} \le x_{es}^{max}I_{es,i,s,w,t}^{dch}\ ;\ z_{es,i,s,w,t}^{dch} \le x_{es,i,t}\ ;\ z_{es,i,s,w,t}^{dch} \ge x_{es,i,t} - \left(1 - I_{es,i,s,w,t}^{dch}\right)x_{es}^{max} \tag{29}$$

Similarly, the product $I_{es,i,s,w,t}^{ch}x_{es,i,t}$ is decoupled by including the following set of constraints:

$$z_{es,i,s,w,t}^{ch} \le x_{es}^{max}I_{es,i,s,w,t}^{ch}\ ;\ z_{es,i,s,w,t}^{ch} \le x_{es,i,t}\ ;\ z_{es,i,s,w,t}^{ch} \ge x_{es,i,t} - \left(1 - I_{es,i,s,w,t}^{ch}\right)x_{es}^{max} \tag{30}$$

The active power limits of existing generators are given by (31). In the case of new generators, the corresponding constraints are (32). Note that the binary variables multiply both bounds to make sure that the power generation variable is zero when the generator remains either unutilized or unselected for investment.

$$P_{g,i,s,w,t}^{E,min}u_{g,i,t} \le P_{g,i,s,w,t}^E \le P_{g,i,s,w,t}^{E,max}u_{g,i,t} \tag{31}$$

$$P_{g,i,s,w,t}^{N,min}x_{g,i,t} \le P_{g,i,s,w,t}^N \le P_{g,i,s,w,t}^{N,max}x_{g,i,t} \tag{32}$$

It should be noted that these constraints are applicable only for conventional DGs. In the case of variable generation sources (such as wind and solar PV), the upper bound $P_{g,i,s,w,t}^{max}$ should be set equal to the minimum of the actual production level at a given hour, which is dependent on the level of primary energy source (wind speed and solar radiation), and the rated (installed) capacity of the generating unit. And, the lower bound $P_{g,i,s,w,t}^{max}$ in this case is simply set to zero.

The set of logical constraints in (33) ensure that an investment decision cannot be reversed. In addition to the constraints described above, the direct current (DC) based network model and radiality related constraints presented in [19] are used here.

$$x_{k,t} \geq x_{k,t-1}; \;\; x_{g,i,t} \geq x_{g,i,t-1}; \;\; x_{es,i,t} \geq x_{es,i,t-1} \tag{33}$$

IV. Results and Discussions

A standard IEEE 33-bus radial distribution network, shown in Fig. 1, is used here for carrying out the required analysis mentioned earlier. The system has a rated voltage of 12.66 kV, and a total demand of 3.715 MW and 2.3 MVAr. Network data and other related information about this test system can be found in [21]. Other data and assumptions made throughout this paper are as follows. The planning horizon is 3 years long, which is divided into yearly planning stages, and a fixed interest rate of 7% is used. The expected lifetime of ESS is assumed to be 15 years while that of DGs and feeders is 25 years. Two investment options with installed capacities of 0.5 and 1.0 MVA are considered for each wind and solar PV type DG units. The installation cost and emission related data of these DG units, provided in [22], are used here. For the sake of simplicity, all maintenance costs of DGs are assumed to be 2% of the corresponding investment costs while that of feeders is 450 €/km/year. The investment cost of each feeder is 38700 €/km. The current limits of all feeders is assumed to be 200 A except for those between nodes 1 and 9 which is 400 A. It is assumed that all feeders can be switched on/off, if deemed necessary.

In addition, it is assumed that wind and solar power sources are uniformly available at every node. The operational variability and uncertainty introduced by wind and solar PV type DGs, demand and electricity price are accounted for via the clustering method proposed in [23]. The maximum allowable bus voltage deviation in the system is set to 5%, and node 1 is considered as a reference with a voltage magnitude of 1.0. Annual demand growths of 0%, 5% and 10% are also considered in all simulations. Emission prices in the first, second and third stages are set to 25, 45 and 60 €/tCO2e, respectively, and the emission rate of power purchased from upstream is arbitrarily set to 0.4 tCO2e/MWh. The cost of unserved energy is 2000 €/MWh. A power factor of 0.9 is considered in the system, and is assumed to be the same throughout. The base power is set to 1 MVA.

The computed values of relevant variables are analyzed for different cases (as depicted in Table I) over the three years planning horizon. Case 1 represents the base case topology where no investments are made while Case 2 considers an optimal reconfiguration but with no investments. Cases 3 and 4 both consider investments in DGs only but differ in that the former does not change the network topology and the latter uses optimal switching. The last two cases correspond to scenarios where investments in DGs are coordinated with that of ESSs. Case 5 uses the topology in the base-case while Case 6 uses network reconfiguration. The results in Table I reveal the significant differences in overall NPV cost in the system, share of energy supplied by RES and ESS combined, cost of total network losses and unserved power among the aforementioned cases. The results are also compared with the base case system where no investments are made and the network topology is held the same. Network reconfiguration alone, as in Case 2, results in about 8.4% in the cost of losses, and a 3.1% reduction in the NPV overall system cost compared with that of Case 1.

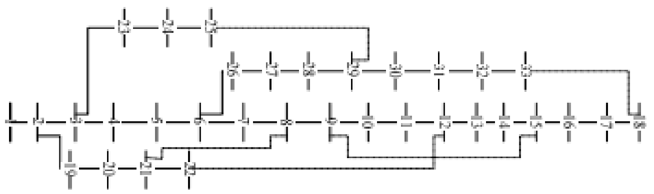

Fig. 1 Single line diagram of the test system in base case.

TABLE I. Results of Relevant Variables for Different Cases

Cases*	Total cost (*TC*) (k€)	Energy supplied by RES and ESS (%)	Total cost of losses (k€)	Total cost of unserved power (k€)	Total installed size (p.u.)		
					Wind	Solar	ESS
1	45447.91	0.0	1089.80	1505.70	0.0	0.0	0.0
2	44044.58	0.0	997.85	0.00	0.0	0.0	0.0
3	33281.50	58.1	433.58	161.79	6.0	3.0	0.0
4	33106.07	58.2	404.59	0.00	6.0	3.0	0.0
5	26522.10	88.8	218.33	0.00	8.0	1.0	3.0
6	26516.52	88.8	212.73	0.00	8.0	1.0	3.0

**Case 1: Base case; Case 2: Optimal switching with no investment; Case 3: DG investment on base case topology; Case 4: DG investment under optimal switching; Case 5: DG and ESS investment on base case topology; Case 6: DG and ESS investment under optimal switching.*

In addition, network reconfiguration avoids a total of 396.3 kVA load curtailment (or 256.9 kVA in Case 3) that would otherwise occur at nodes 17, 18, 32 and 33 due to voltage limit constraints in Case 1.

Another more interesting observation from Table I is that Cases 3 and 4 result in (approximately) 60% reductions in the overall cost of the system and the amount of imported energy. Wind and solar power sources are complementary by nature. This important phenomenon seems to be exploited when DG investments are not accompanied by investments in ESSs (i.e Cases 3 and 4). This is because, according to the DG investment solution in Table I, the operational variability in the system seems to be handled by investing an appreciable amount in both complementary power sources (wind and solar). This can also be seen from the level of demand covered by RESs, which is about 58%.

The results corresponding to Cases 5 and 6 show that the total cost and cost of losses are dramatically reduced by more than 41.6% and 80% respectively. This reveals the substatial benefits of coordinating investments DG with ESSs. Generally, ESSs significantly improve system flexibility, enabling large-scale accommodation RES energy. Interestingly, the total amount of installed DGs (9 MW) is the same for Cases 3—6 i.e. with/without ESSs. Even if this is the case, in the absence of ESSs (Cases 3 and 4), there may be spillage of RES power when the demand is lower than the total generated power. However, the installation of ESSs leads to an efficient utilization of RES power. This is evident from the amount of energy consumption covered by the combined energy supplied by RESs and ESSs in Cases 5 and 6 is about 89%. Normally, network switching capability also improves system flexibility, leading to a high level RES penetration. In this particular study, the effect of network switching on the level of RES power absorbed by the system is not significant as one can observe in Table I. This may however be case-dependent. A more frequent switching capability could, for instance, have significant impact.

The optimal location and size of installed DGs corresponding to Cases 3 through 6 is shown in Fig. 2. The average voltage profiles at each node and for each case are depicted in Fig. 3. It is interesting to see in this figure the substantial contributions of DGs and ESS installations to voltage profile improvement. As shown in Fig. 3, the coordinated integration of DGs and ESSs (i.e. Case 6), especially leads to the best voltage profile. Fig. 4 demonstrates the optimal network topology, DG and ESS locations corresponding to this case. The benefit of joint DG and ESS investments along with network reconfiguration in terms of losses reduction (over 84% on average) can be seen from Fig. 5. The spikes observed in Case 6 are because of the variability in RES power injected into the system.

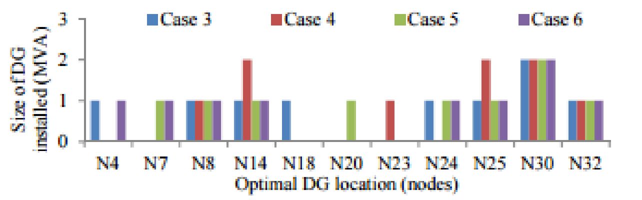

Fig. 2 Optimal placement and size of DGs under different cases.

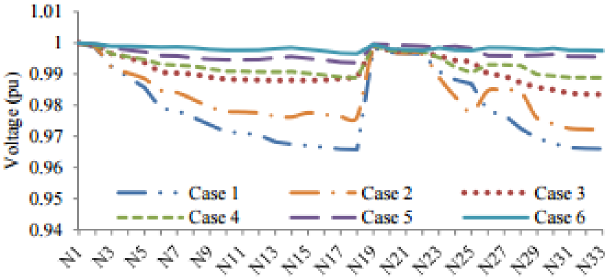

Fig. 3 Average voltage profiles in the system under different cases.

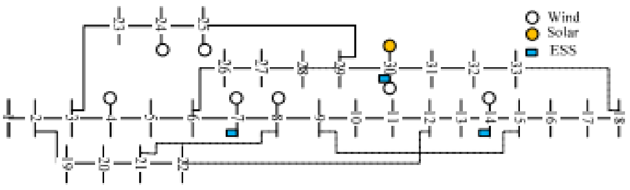

Fig. 4 Optimal locations of DGs and ESSs under Case 6 (*Opened switches 28-29, 8-21, 9-15, 18-33, 12-22*).

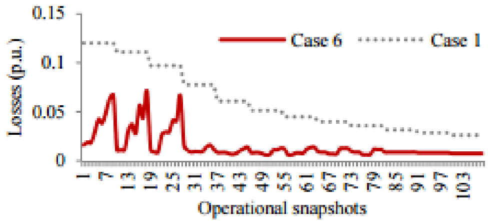

Fig. 5 Total system losses profile.

V. Conclusions

This paper has investigated the impacts of installing DESSs as well as network switching and/or reinforcement on the level of renewable power integrated in the system. A mixed integer linear programming (MILP) model was developed for this purpose, which involves joint optimization of placement and sizing of RES-based DGs and ESSs in coordination with optimal network switching. Numerical results showed the capability of ESSs integration in dramatically increasing the level and optimal exploitation of renewable DGs. According to the simulation results, the simultaneous integration of DGs and ESSs resulted in an overall cost and average losses reduction of 41% and 84%, respectively. The optimal network reconfiguration, DG and ESS installations (jointly or separately) substantially contributed to voltage stability. In the particular case study, the impact of network switching on RES power integration was not significant. However, it should be noted that this can be case-dependent.

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