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Ph.D. Dissertation

OPERATION AND PLANNING MODELS IN FUTURE DISTRIBUTION NETWORKS WITH RENEWABLE ENERGY, ENERGY STORAGE AND ELECTRIC VEHICLES

A Thesis submitted by Pilar Meneses de Quevedo for the degree of
Doctor of Philosophy

Supervised by:
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"Essentially, all models are wrong, but some are useful."
George E. P. Box

To all my family, especially my parents.
A toda mi familia, especialmente a mis padres.

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Abstract

Traditional models have not yet been adapted to account for new resources available to operators and planners in distribution systems. Due to that reason, this thesis explores the use of mathematical models and innovative tools for the leading distribution networks, allowing for a substancial penetration of renewable energy with the integration of generic energy storage devices and electric vehicles in the system. This work focuses on the operation and planning of electric power distribution systems aiming at (a) establishing new management tools for the new framework, (b) optimizing the operation and investment in network assets, renewable generation, upcoming storage devices and charging facilities for the electric vehicles, and (c) guaranteeing the continuity and quality of service in the system. Stochastic methods have been applied in the optimization in order to obtain the best solution taking into account certain degrees of unpredictability or randomness. The proposed models are validated and examined exhaustively in order to demonstrate that the new resources that will dominate future distribution systems can provide benefits to power systems.

Resumen

Los modelos tradicionales todavía no han sido adaptados para tener debidamente en cuenta los nuevos recursos disponibles para los operadores y planificadores del sistema de distribución. Por esa razón, esta tesis explora el uso de modelos matemáticos y herramientas innovadoras para las redes de distribución líderes, permitiendo una penetración sustancial de energía renovable con la integración de dispositivos de almacenamiento de energía genéricos y vehículos eléctricos en el sistema. Este trabajo se centra en la operación y planificación del sistema de distribución con el objetivo de (a) establecer nuevas herramientas de gestión en el marco energético reciente, (b) optimizar la operación e inversión en activos de red, generación renovable, inminentes dispositivos de almacenamiento e instalaciones de carga para el vehículos eléctricos, y (c) garantizar la continuidad y calidad del servicio en el sistema. Se han aplicado métodos estocásticos en la optimización para obtener la mejor solución, teniendo en cuenta ciertos grados de imprevisibilidad o aleatoriedad. Los modelos propuestos han sido validados y examinados exhaustivamente para demostrar que los nuevos recursos que dominarán los sistemas eléctricos de distribución futuros pueden proporcionar beneficios a los sistemas eléctricos.

Abbreviations

AC:	Alternative Current
ARMA:	Auto Regressive Moving Average
BB-BC:	Big Bang-Big Crunch
CA:	Contingency Analysis
CDF:	Cumulative Distribution Function
CCP	Chance Constrained Programming
DC:	Direct Current
DER:	Distributed Energy Resources
DG:	Distributed Generation
DP:	Dynamic Programming
DR:	Demand Response
DS:	Distributed Storage
DSEP:	Distribution System Expansion Planning
DSO:	Distribution System Operators
EDS:	Electric Distribution Systems
EDSO:	European Distribution System Operators
ENS:	Energy Non Supplied
ESS:	Energy Storage Systems
EV:	Electric Vehicles
EVCS:	Electric Vehicle Charging Stations
GA:	Genetic Algorithm
LP:	Linear Programming
MC:	Monte Carlo
MILP:	Mixed-Integer Linear Programming
MINLP:	Mixed-Integer Non Linear Programming
MV:	Medium Voltage
NLP:	Non-Linear Programming
OPF:	Optimal Power Flow
PDF:	Probability Density Function
PF:	Power Factor
POPF:	Probabilistic Optimal Power Flow
PSO:	Particle Swarm Optimization
PV:	Photovoltaic Generation
PWL:	Piecewise Linearization

RES:	Renewable Energy Sources
RDS:	Reconfiguration of Distribution Systems
SOC:	State of Charge
TS:	Tabu Search
V2G:	Vehicle to Grid
V2H:	Vehicle to Home
W2E:	Waste to Energy

Contents

Chapter 1

Introduction

European legislation (Directive 2009/72/EC) defines distribution as "the transport of electricity on high-voltage, medium-voltage and low-voltage distribution systems with a view to its delivery to customers". Distribution System Operators (DSO) are understood as "natural or legal persons responsible for operating, ensuring the maintenance of and, if necessary, developing the distribution system". Article 29 of this Directive does also explicitly allow for combined transmission and distribution system operators. However, in most Member States, Transmission System Operators and DSO are separate entities.

Distribution networks comprise many components like substations, transformation centers, transformers, feeders, branches, nodes, circuit breakers, disconnectors, switches, protection devices and other assets used to keep grid power flowing. Traditionally, as shown in Figure 1.1, distribution networks have been operated either as open rings or as radially-fed networks. Both network topologies use components with basic protection such as reclosers, sectionalisers and fuses, with limited or no automation built in. Due to various technical reasons, electric distribution systems (EDS) usually operate with a radial topology, even though they have a meshed topology, due to two important factors: (a) to facilitate coordination and protection and (b) to achieve a reduction of short-circuit current in EDS. Distribution system configuration is defined by the state (open/closed) of the connections of each branch terminal to the system nodes.

Generally, in traditional networks, DSO are not fully aware of disturbances. In conventional networks time-consuming manual labor is needed to locate and restore supply after a fault has occurred. In the last few years, the classic planning model and the technology for supplying electrical energy have changed due to many external influences. They assume tasks including simple reading, fault location, interference detection and power quality analysis for a complete remote control or even automated operation. Additionally, distribution systems have grown in complexity, as more and more distributed generation (DG) is being introduced.

What is DG? DG is a small-scale set of technologies dedicated to producing electricity close to the end-users demand. DG technologies often consist of non-renewable and renewable energy generators offering a number of potential bene-

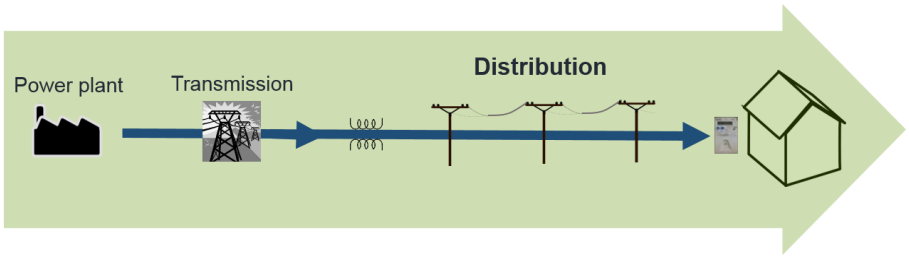

Figure 1.1: Traditional electric distribution system. Source: European Distribution System Operators (EDSO) for smart grids, https://www.edsoforsmartgrids.eu/.

fits. In many situations, DG can contribute to have lower-cost electricity, higher power reliability and more security with fewer environmental consequences than large-scale traditional power generators, increasing the energy and environmental performance. In contrast to the approach used in the traditional electric power paradigm, DG systems employ numerous small plants and can provide power on-site with little dependence on the grid.

Why DG? DG is a real and efficient alternative to the centralized model characterized for having small power generation facilities. DG has great potential and it can achieve important goals. These include reduction of both losses and investment cost in distribution networks, improvement of continuity of supply, support for the system at peak periods, and, above all, energy autonomy. In addition, DG, especially renewable energy sources (RES), supports climate change management. In this regard, the Kyoto Protocol on climate change is an international agreement whose main objective is to reduce the emission of greenhouse gases into the atmosphere. This agreement has promoted the development of renewable energy since 2005. The second period of the Kyoto Protocol, which spans until 2020, will lead to the development of renewable technologies. Renewable generation, mainly wind power and photovoltaic, consists of small-scale technologies connected at the distribution level.

The most important benefits of DG, mainly RES, are the following: power loss reduction in most cases, voltage profile improvement, improvement of power quality, fuel cost reduction due to increased overall efficiency, transmission and distribution cost savings, CO_2 emission reduction and a decrease in the electricity price. The main drawbacks are: production uncertainty, bidirectional flows, voltage fluctuations and the need for new protection schemes.

DG directly influences the energy flow in the distribution network, as well as the electrical parameters used for the protection schemes, as they were not initially designed to incorporate DG. A grid code has a significant role in the integration paradigm of DG, especially RES, due to its own characteristics. A grid code is basically a set of technical conditions and requirements to be followed when connecting generators. Its elaboration usually implicates DSO. Therefore, DSO

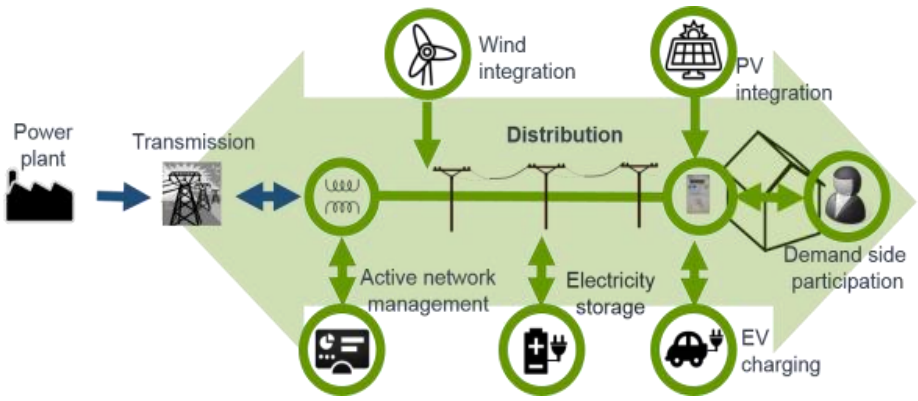

Figure 1.2: Future electric distribution system. Source: EDSO for smart grids, https://www.edsoforsmartgrids.eu/.

must adapt the design and operation of their networks via efficient intervention techniques, alternative to traditional reinforcement, to enable the networks to facilitate efficient connection of new sources, while maintaining the stability, the power quality and network voltage within its limits. In this way, energy systems are moving from static and centralised architectures towards more flexible, automated and distributed structures. New approaches for protection may be needed, independent from network topology and the number of power generation points. The combination of the need to include more sophisticated monitoring and control systems and the introduction of RES is creating a challenging environment for the future distribution networks.

Future distribution systems, as seen in Figure 1.2, are often referred to as smart grids where more intelligent technologies are integrated into the system to monitor, control and operate the whole system. These electricity networks can efficiently manage the power supplied to all the users connected, consumers, and prosumers to ensure economic, efficient and sustainable power systems with low losses and high levels of quality and security of supply and safety. Power system islanding, both intentional and unintentional, is traditionally considered one of the most critical operation conditions. Controlled islanding operation of distribution systems having a significant penetration of RES is becoming an important option for economic and technical reasons. Implementation of intentional islanding of RES has the purpose to improve the continuity of supply and reliability of the power system.

Security assessment plays an important role in power distribution networks. Particularly, contingency analysis provides a decision-aid tool to mitigate potential failures in distribution networks and analyze their behaviour in case of outages in electrical components. This tool provides a contingency selection and evaluation method to check violations in the network, solving the resulting power flow and

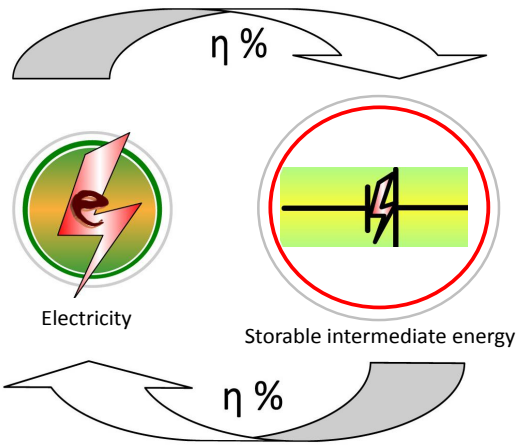

Figure 1.3: A generic storage system efficiency diagram. Source: E.M.G. Rodrigues et al., Energy storage systems supporting increased penetration of renewables in islanded systems. Energy, vol. 75, pp. 265-280, August 2014.

providing reconfiguration solutions if an outage occurs. In future distribution networks this tool should integrate RES and other new sources in active distribution systems. Furthermore, the knowledge of the reliability of a distribution system is an important issue in system planning and operation for the development and improvement of the system. To achieve a minimum number of interruptions for customers, utilities should make an effort to improve reliability. It is a known fact that most customer interruptions are caused by a failure in the distribution system. The evaluation of the probability distributions of reliability indices are commonly based on simulations. To this regard, random events like the occurrence of a fault or the time to restore the service after a fault are presented in this thesis.

Energy Storage Systems (ESS) are one of the most important elements for the future electricity grids. ESS refer to the process of converting electrical energy from a power source or network into another form (chemical, mechanical, thermal, magnetic) that can be stored in order to be converted back into electrical energy afterwards when needed (see Figure 1.3). An ESS is characterized by many features, such as its electrical capacity, efficiency, charge/discharge behaviour, lifetime, depth-of discharge, cost and location. Basically, the advantages offered by ESS can be economic and technical. On the one hand, ESS can help to improve profitability to the power system's stakeholders; on the other hand, ESS may provide reliability, safety and productivity.

The emerging opportunity for electric vehicles (EV) is also explored in this thesis. EV have the potential to contribute significantly to solving current and future environmental challenges due to the existence of ambitious carbon reduction and sustainability targets. The massive increased demand of electricity due to the need for charging requirements of EV will have a significant impact on electricity

Figure 1.4: Electric vehicle charging station. Source: G.R. Chandra Mouli et al., System design for a solar powered electric vehicle charging station for workplaces. Applied Energy, vol. 168, pp. 434-443, April 2016.

system operation and recharging infrastructure (see Figure 1.4). This impact will depend on many different aspects, such as EV penetration, location of the charging points, power supply of the chargers, charging mode, and consumers' driving patterns among others. All the new resources like RES, ESS and EV, that which progressively increase their penetration in the power system, will be part of the future distribution systems, so the operation and planning models should take them into account.

1.1 Motivation

Different reasons have led to focusing on the importance of DG, mainly RES, in distribution systems in order to achieve targets related to fossil energy independence and emission reduction. The safe integration of renewable energy is one of the major challenges for the operation and planning of EDS. In addition, forecasts indicate a moderate growth in demand, a strong increase of RES and EV, and a need for firm and flexible electric power. ESS are becoming an important source in tems of energy flexibility. Consequently, distribution networks have to be adapted and transformed in order to meet the new challenges of the future.

Recently, due to the increase of DG penetration, distribution grids have become active networks. The presence of bidirectional flows can impact the quality of power supply, in particular the voltage levels, and produce an increase in short-circuit capacity. One challenge is to model the power flow in distribution networks including bidirectional flows. This must be taken into account by DSO to monitor, simulate and manage the network from both technical and economic viewpoints. Even though EDS have a meshed structure, as already mentioned, the great ma-

jority of practical distribution systems are operated radially due to the simplicity of handling and creating openings at certain locations using switches in the grid. Therefore, it is necessary to reconfigure the network in order to find the best topology of the system achieving the lowest power losses, a high load demand supply and an efficient operational performance considering the integration of RES connected to the traditional distribution networks.

Thus, reconfiguration of distribution systems (RDS) can be used to improve their operation, particularly considering both RES and ESS. The combination of RES and ESS in electrical networks creates an opportunity to integrate them within EDS, taking advantage of them in normal and abnormal conditions, like contingencies and islanding. In these situations, imbalance between supply and demand leads to several problems, such as frequency and voltage deviation in the power grid, making it necessary to apply a procedure capable of keeping the islanded area energized. Thus, microgrids are emerging as viable network structures to serve the local demand that operates connected to the traditional centralized electrical grid normally, but can be disconnected and operated autonomously. The concepts used to operate a microgrid can be adopted to determine how to manage an intentional island as a subsystem of a distribution network to be managed during the restoration process after a fault.

Other issues are related to the nature of RES, due to its intermittency and uncertainly, in particular wind power. Accordingly, based on regulation, the system operator has the right to curtail wind power in order to avoid any violation of the system's constraints. The reason for combining RES and ESS is to improve reliability and reduce power imbalance, avoiding demand and wind curtailment. For these reasons, in the new context of RES uncertainty, the physical placement of both renewable and storage units must be studied in order to plan the operation in short-term. One of the ambitions of this thesis is to focus on showing the effects of combining RES with ESS when minimizing overall costs in order to decrease operational costs, power losses, wind curtailment and demand curtailment.

Future decisions in the optimal expansion planning of distribution systems should also deal with the imminent penetration of EV that will increase the uncertainty associated to the charging demand. In this way, the study of EV decision models should be performed in order to model EV's charging demand in the future and to determine the best location for new feeders, substations, RES, ESS and EV charging stations (EVCS). The development of a new methodology is necessary to include efficient renewable generation units and EV charging demand stochasticity in the traditional expansion planning of substations, transformers and feeders.

Consequently, with this new paradigm, it is necessary to thoroughly review the management of the distribution networks, applying operation and planning tools to maintain the quality and continuity of supply at the lowest possible cost, also considering the modeling of the stochasticity in both operation and planning. This process takes place in several phases, depending on the time scale affected. In this context of active distribution networks and microgrids, new operation and planning models are presented in order to solve the new structural, economic and technical problems of future distribution networks.

The procedures applied in the work developed in this thesis are focused on four

main issues:

1. Optimizing the real-time operation of an active distribution network for contingency and unintentional islanding response.

2. Optimizing the short-term operation planning of the distribution network for wind curtailment mitigation due to the co-optimal location of wind power generation and ESS.

3. Optimizing the long-term expansion planning of the future distribution network including RES, ESS and EV.

4. Evaluating the reliability for each type of user within a microgrid framework. The evolution of distribution automation, distributed energy resource control, computational methods and data analytics is making it possible to introduce a number of additional features into the classical reliability analysis tools.

1.2 Research Hypotheses

This thesis considers the DSO as an entity entrusted with the expansion planning of the distribution network including generation and the coordination of the technical operation of the system guaranteeing the continuity and quality of supply. This thesis focuses on the optimal cost minimization of the operation and planning of distribution systems from a joint generation and distribution strategy, so as to achieve a good integration of RES, ESS and EV. Accordingly, the included cost model considers both the energy production and network costs for each specific operation and planning tools.

Medium-voltage networks are modeled as balanced 3-phase systems represented by an equivalent one-phase system. Additionally, an Alternative Current (AC) power flow is implemented and linearized so that the global optimal solution is obtained. Islanded radial operation of the system is possible with DG integration in the case of anomalous conditions, where faults are considered in feeders and circuit breakers. The wind power curve is approximated by a linear function between power and wind speed within the interval between the cut-in wind speed and rated power speed, being constant from this value until the cut-out wind speed is reached. The linearization of the power curve provided by manufacturers is as follows (1.2.1):

$$P_{wd} = \begin{cases} 0, & \text{if } v < v_l \\ \frac{P_r}{(v_r - v_l)} v + P_r(1 - \frac{v_r}{(v_r - v_l)}), & \text{if } v_l < v < v_r \\ P_r, & \text{if } v_r < v < v_0 \\ 0, & \text{if } v > v_0 \end{cases} \tag{1.2.1}$$

where v is the wind speed (m/s), v_l is the cut-in wind speed (m/s), v_r is the rated wind speed (m/s), v_0 is the cut-off wind speed (m/s), P_r is the rated electrical power (kW) and P_{wd} is the output power of the wind turbine (kW).

Reactive compensation of wind turbines is generally assumed in order to keep the power factor of the distribution network within the limits established in the operational procedures of the DSO, allowing for the existence of capacitor banks connected to the wind generators.

The load profile changes in each time interval. The considered period of time depends on the type of model implemented. In real-time operation models, 1 hour has been considered with 10-minute intervals. In the short-term operation planning model, 1 week is used with 1-hour intervals. The evaluation of reliability is performed in a mid-term planning model considering 1 year discretized in 1-hour intervals. Lastly, the long-term planning model is implemented for 15 years with 5-stage intervals.

A generic storage device is introduced in the operation and planning models as a unit with the capability of converting and storing energy (charging), and reverting the process by injecting back (discharging) the stored energy to the distribution system as shown in Figure 1.5. We assume some simplifications in order to include ESS in the distribution system:

- Conversion losses are considered in the efficient rates of production and storage processes. These rates are given with respect to the energy measured at the node connected to the ESS.
- Stored energy losses are not considered. For instance, sulfation and grid corrosion in lead-acid batteries, evaporation or filtration in pumping stations.
- Energy storage/production occurs at constant power for a certain period (10 minutes, 1 hour, etc.).
- There is no hysteresis loop in charging or discharging.
- There are no up or down ramps.

Moreover, the consideration of EV in the long-term planning model is based on realistic EV statistics to calculate the total charging demand for all EV. This data includes information of each household, type of vehicle, trip distance, start and end time, month, day of the week, and trip purpose, among others. Due to the lack of data of EV travel patterns, we assume them to be the same as the traditional fossil-fueled ones. First, we exclude the trips with a mileage greater than the maximum mileage possible using electricity. A trip is the journey done by a vehicle when it goes from the drivers' home to his/her workplace, or a commercial area, and vice versa. We assume that all EV are fully charged at the beginning of the first trip. Different battery capacities are assigned randomly considering a normal power supply at the EVCS. These charging facilities are assumed to be connected at a medium-voltage connection point. A novel vehicle decision algorithm is implemented in order to compute the total EV charging demand for all the vehicles per hour, day, month and time stage (year) for the entire system.

The greatest challenge for the planner and operator is to integrate everything in the best possible optimal and effective way with the aforementioned hypotheses.

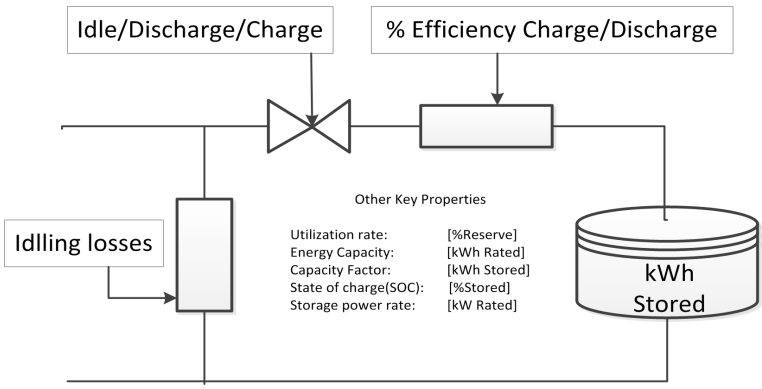

Figure 1.5: Generic storage device structure. Source: Miguel Asensio et al., Smart and Sustainable Power Systems: Operations, Planning, and Economics of Insular Electricity Grids, Chapter 6: Electric Price Signals, Economic Operation, and Risk Analysis, edited by João P. S. Catalão, pp. 285-344, 2016, CRC PRESS, ISBN 978-1-4987-1212-5.

1.3 Objectives

The main objective of this doctoral thesis is the establishment of mathematical models that permit the minimization of the operation and planning costs of distribution networks and show the way for future distribution systems. Additionally, an analysis is performed considering both the technical and economic viewpoints through the development of mathematical tools to stress the relevance of the decisions of the DSO in the future grids. Similarly, the technologies that are gradually growing in distribution networks, like ESS and EV, are also subject of study. Therefore, objectives such as modeling EV charging demand and analyzing the behaviour of ESS are also part of this thesis.

In real-time operation, the goal is the optimal operation of the distribution system with RES and ESS under abnormal conditions. In the short-term operation planning this thesis focuses on the optimal co-location of RES and ESS. In the long-term, the goal is the optimal planning of the joint expansion of the network, including RES, ESS, and EV. Finally, the last research target is the evaluation of reliability through sequential Monte Carlo (MC) simulation.

The specific objectives are presented below and they are intimately related with the five papers presented in the next sections.

1.3.1 Contingency Assessment and Distribution Network Reconfiguration in Distribution Grids Including Wind Power and Energy Storage

- To provide a tool to study the contingencies in distribution networks analyzing their behaviour in case of outages in the system.

- Strategies for reconfiguring the distribution system are established concerning power losses, non-supplied energy and wind curtailment minimization.

- To analyze the behaviour of ESS, to see how the scheduled program changes under contingencies, and to study the benefits of the combination of ESS and wind power generation.

- To enable the operation of radial islands that are disconnected from the main grid (substation) due to the existence of a fault in a branch that isolates part of the network downstream from the fault.

- The objective of the mathematical model developed consists of the minimization of switching costs, scheduled production and storage cost function, network costs and corrective action costs.

1.3.2 Islanding in Distribution Systems Considering Wind Power and Storage

- To define a predefined procedure capable of managing the network when an electric island is formed and separated from the external grid.

- To present a novel algorithm to keep the load and generation units on-line under islanding conditions with respect to the total power imbalance of the isolated area.

- The objective of the mathematical model developed consists of the minimization of operational storage system costs, wind and demand curtailment, power losses and voltage deviation of buses.

1.3.3 Optimal Placement of Energy Storage and Wind Power under Uncertainty

- To provide a method that can optimally locate both ESS and wind power units considering the uncertainty associated to the nature of wind, load and the cost of the energy purchased at the substation. In addition, the model aims at minimizing the overall operational costs.

- To simulate and analyze different cases showing the importance of ESS units with several power capacities and maximum production and storage power, in order to avoid wind curtailment.

- The objective of the mathematical model developed consists of the minimization of network (losses and voltage deviation) costs and production (substation energy production, wind curtailment, and ESS production and storage) costs.

1.3.4 Impact of Electric Vehicles on the Expansion Planning of Distribution Systems Considering Renewable Energy, Storage and Charging Stations

- To implement a multi-stage planning tool that meets a growing demand at each stage and includes the most relevant RES as wind power generation and photovoltaic panels, ESS units, and EV charging demand.
- To analyze and study the importance of integrating ESS in distribution and generation system expansion planning in the presence of EV. Furthermore, medium-voltage EVCS should be appropriately located and sized in order to minimize the present value of the generation and distribution network costs.
- To model the EV charging demand through a novel method. The uncertainty associated to the unpredictable sources is also modeled and included in the model through a set of scenarios with a clustering technique.
- The objective of the mathematical model developed consists of the minimization of the present value of the total cost: investment cost and operational costs (maintenance, production, energy losses, unserved energy costs).

1.3.5 Reliability Assessment of the Microgrids with Local and Mobile Generation, Time-Dependent Profiles, and Intra-Day Reconfiguration

- To implement a sequential MC method that evaluates and analyzes the reliability in the operation of distribution networks calculating the energy non supplied (ENS). This ENS is calculated through 3 different approaches for each type of consumer.
- To simulate the behaviour of the formation of autonomous islanded subsystems in the case of the existence of permanent faults. An explanation of how they are formed and how they are reconnected afterwards to the main grid is also included.
- The algorithm procedure is explained in detail in order to determine the total duration of the interruptions.
- To obtain the solution and show different case studies either with or without both DG and mobile generation using a probabilistic approach.

1.4 Methodology

The thesis focuses on the optimal management of the operation and planning of distribution networks with the integration of renewable energy, ESS and EVCS through the use of mathematical tools. Undoubtedly, the main issue associated to the future distribution networks is the unpredictability of wind, solar radiation, market prices and the transition to EV, especially in the long term. Uncertainty

may be due to lack of reliable data, measurement errors or parameters that represent information about the future. In addition, RES are intermittent so the analysis of the characteristics of integrating ESS devices is studied in detail in the operation and planning of the system. To perform this study, a methodology based on stochastic programming has been followed in order to consider the uncertainties mentioned, facilitating the resolution and analysis based on the hypotheses assumed.

This work primarily deals with optimization models implemented in the GAMS software. Stochastic integer programming problems combine the challenges of stochastic programming with integer programming. Mixed-integer linear stochastic programming is used due to the existence of binary variables in the mathematical formulation of the models. Besides, a linearization procedure is performed for the non-linear expressions in order to guarantee the optimal global solution. To cope with this, both a piecewise linearization and an approximation due to the multiplication of two variables are applied. In the real-time models presented in this thesis, a two-stage mixed-integer linear stochastic programming model is proposed. This model can be applied to problems that deal with "here-and-now" decisions, which have to be taken on the basis of prior existing information about future situations without additional observations. The first-stage decisions do not depend on the scenario that will actually occur in the future. The second-stage decisions are the resources that can be used for each possible future scenario. This second-stage is called "wait-and-see", "scenario analysis" or "what-if-analysis", where the decisions taken depend on the future realization of the scenario. The general two-stage linear stochastic programming problem is formulated in equation (1.4.1):

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & c^T x + E_\xi |Q(x, \xi| \\ \text{subject to} \quad & Ax = b \\ & x \geq 0 \end{aligned} \tag{1.4.1}$$

where $Q(x, \xi)$ is the optimal value of the second-stage problem (1.4.2):

$$\begin{aligned} \underset{y}{\text{minimize}} \quad & q(\xi)^T y \\ \text{subject to} \quad & T(\xi)x + W(\xi)y = h(\xi) \\ & y \geq 0 \end{aligned} \tag{1.4.2}$$

In such formulation $x \in R^n$ is the first-stage decision variable vector, $y \in R^n$ is the second-stage decision variable vector, and $\xi(q, T, W, h)$ contains the data of the second-stage problem. In this formulation, a "here-and-now" decision, x, is made at the first stage before the realization of the uncertain data, ξ, is known. At the second stage, after the realization of ξ becomes available, an appropriate optimization problem is solved.

At the first stage, the first-stage cost, $c^T x$, plus the expected cost of the optimal second-stage decision, $E_\xi |Q(x, \xi|$, are optimized. The second-stage problem can be simply viewed as an optimization problem which describes a supposedly optimal

behavior when the uncertain data ξ are revealed. Matrices T and W are called technological and recourse matrices, respectively.

Moreover, in short-term operation and in long-term planning models, a multi-objective scenario-based stochastic programming model is proposed. The generic formulation is shown in equation (1.4.3):

$$\underset{y}{\text{minimize}} \quad f(x) = f_1(x), f_2(x), ..., f_k(x)^T \tag{1.4.3}$$

where $x = x_1, x_2, ..., x_n$ is the vector of decision variables.

The method used to address the problem of having conflicting objectives is based on the combination of objectives. The weighted-sum method can be applied, in which the value obtained by adding the values corresponding to the different objectives, each one multiplied by a weight coefficient, is optimized. These weight coefficients establish the relative importance of each objective. The multiobjective optimization problem is thus transformed into a scalar optimization problem of the form shown in equation (1.4.4):

$$\underset{y}{\text{minimize}} \quad \sum_i \omega_i f_i(x) \tag{1.4.4}$$

where ω_i is the positive weight coefficient corresponding to objective i.

Regarding the simulation models, a medium-term reliability assessment operation procedure is developed using the MATLAB software. The specific methodologies applied for both the optimization and simulation models are described below.

1. **Real-time Optimization model**

   Contingency Assessment and Distribution Network Reconfiguration in Distribution Grids Including Wind Power and Energy Storage

   At the first stage, only contingency conditions regardless of the scenarios are considered, including switching cost and scheduled production and storage costs.

   At the second stage, minimization of power losses, production at the substation, curtailment, and real-time production and storage costs dependent on the scenarios are taken into account.

   Islanding in Distribution Systems Considering Wind Power and Storage

   At the first stage, the variable that remains invariant regardless of the scenario is the switching cost.

   At the second stage, minimization of power losses, voltage deviation, curtailment, and real-time production and storage costs dependent on the scenarios are considered.

2. **Short-term Optimization Model**

Optimal Placement of Energy Storage and Wind Power under Uncertainty

For the short-term operation planning, the proposed model is a one-stage multiobjective stochastic program transformed to a probabilistic single objective one based on the combination of objectives, each one multiplied by its corresponding associated probability.

The probability weighted average of all the possible values produces the expected value of power losses, voltage deviation, production at the susbtation, wind curtailment costs, and production and storage costs.

3. **Long-term Optimization Model**

   Impact of Electric Vehicles on the Expansion Planning of Distribution systems Considering Renewable Energy, Storage and Charging Stations

   A multi-stage multi-objective stochastic programming model is formulated as a mixed-integer linear program.

   The model minimizes the present value of the total expected cost: investment cost, maintenance cost, production cost, cost of energy losses and unserved energy costs.

4. **Simulation Model**

   Reliability Assessment of Microgrids with Local and Mobile Generation, Time-Dependent Profiles, and Intra-Day Reconfiguration

   Finally, in addition to the optimization models, a simulation algorithm without an objective function has been developed with the sequential MC method.

Another aspect to deal with is the creation of scenarios for each optimization model. In the real-time N-1 contingency operation model, the scenarios are implemented under an estimated cone of uncertainty over a known wind power value in the instant when a contingency happens. These scenarios are created with MC simulation under this cone of uncertainty. Afterwards, the number of scenarios is reduced using a k-means classical clustering technique in order to obtain a faster solution. In the real-time islanding operation model, a probabilistic method based on time series has been implemented for wind generation scenarios based on a classical mechanism, as it can be seen in chapter 3.

For the short-term operation planning model, the same probabilistic method based on time series is developed for 3 uncertainty parameters. Then, the different scenarios for each uncertain parameter are reduced by using a clustering technique so as not to increase the computational time excessively. Finally, the relationship between the three sources of uncertainty is considered though a scenario tree. All possible combinations of the uncertain parameters allow us to represent all scenarios in a tree with its associated probability.

For the long-term planning model, the k-means++ methodology arranges the hourly data into operating conditions representing the different scenarios for all the uncertain parameters. K-means is an unsupervised classification algorithm that

groups objects in k groups based on their characteristics. The grouping is done by minimizing the sum of distances between each object and the centroid of its group or cluster. K-means++ allows us to obtain a better initial set of centroids.

More details about scenario generation are explained in the different sections of the following chapters.

The set of procedures that allow us to model and solve the operation and planning problems in this thesis are the following:

- A review of the recent literature related to the technical performance of the different technologies considered: wind power generators, photovoltaic solar panels and ESS units.
- A review of the recent literature comparing the different techniques of contingency analysis and behaviour assessment of power networks under N-1 contingencies.
- A review of the recent literature about the optimization methods that have been presented to solve the RDS problem.
- Modeling, simulation and analysis of the contingency and reconfiguration model including and comparing the performance of wind power and its combination with ESS.
- A review of the recent literature dealing with the disconnection from the bulk power system creating islands, either intentional or unintentional. Control techniques under islanding conditions are studied.
- Modeling, simulation of predefined islanded areas and analysis of active power balancing and storage behaviour.
- A review of the state-of-the-art models and optimization methods applied to DG location, ESS placement and the co-location of both technologies.
- Modeling, simulation and analysis of the different case studies with different installed wind capacity levels, ESS capacities and ESS maximum power.
- A review of the state-of-the-art of the classical reliability methods, also considering DG. Study of the emergent practices in the smart grid context.
- Modeling, simulation and probabilistic analysis of the reliability results, either considering DG or not, and with or without mobile generation.
- A review of the expansion planning models from the recent literature including different technologies such as RES and ESS in which is it possible to invest.
- A review of the recent literature related to EV charging models and EVCS expansion planning in distribution systems.
- Modeling, simulation and analysis of multistage expansion planning with stochasticity of RES, EVCS and a comparison when considering the possibility to invest in ESS.

1.5 Literature Review

A detailed literature review of the existing literature has been carried out, mainly focusing on recent publications regarding real-time, short-, medium- and long-term operation and planning models. Likewise, the impact of integrating new sources such as RES, generic ESS and EV into distribution networks has been examined.

The penetration of RES, especially wind power, can cause several problems due to its uncertainty and intermittency [1]. Recently, in modern power systems, storage devices have grown rapidly. ESS are integrated into EDS to consider several purposes such as smoothing output power of RES, improving distribution system reliability, meeting real-time demand and being economically efficient [2].

For the resolution of all the models presented in this thesis and their analysis, software tools such as GAMS [3] and MATLAB [4] are used.

1.5.1 Real-time operation models

Several studies have been carried out to assess contingencies, reconfiguration and islanding problems in electrical networks, both in transmission and distribution. Two different types of optimization methods have been used: 1) exact optimization techniques that guarantee finding an optimal solution and 2) heuristic and metaheuristic optimization methods where there is no guarantee that an optimal solution can be found.

In literature, exact techniques such as branch and bound are used for contingency analysis: deterministic mixed-integer linear programming [5], [6], [7], [8], probabilistic mixed-integer linear programming [9], mixed integer non-convex programming [10], quadratic programming [11], two-stage deterministic programming [12], stochastic programming [13], learning data mining decision tree algorithm [14], and bi-level programming [15]. Likewise, heuristic methods such as tabu search algorithms [16], [17] and genetic algorithm [18], or metaheuristic methodologies such as artificial intelligent Petri nets [19] and hybrid algorithms [20] have been implemented for the analysis of contingencies. In terms of behavior assessment of power networks, an N-1-1 contingency-constrained unit commitment is studied in [5], additionally [6], [8] include renewable generation in the model. In [7], a method for contingency-constrained transmission capacity expansion planning is developed, in which a contingency identification index detects these lines and creates variable contingency lists for different network loading conditions. In [9], a multi-period interval unit commitment optimizing the generation schedule taking into account the probabilistic nature of generation and transmission contingencies is proposed, as well as the post-contingency energy redistribution. In addition, in order to evaluate the performance of the power network, a total supply capability is considered in [10] to cover N-k transformer contingencies, and a robust evaluation is proposed while considering the effect of topology reconfiguration. In [16], multiple high-quality corrective switching actions for contingencies with potential violations are studied. To reduce the computational complexity, three heuristic algorithms are proposed to generate a small set of candidate switching actions. In [17], an AC-based real-time contingency analysis with transmission switching

is implemented. In [19], an artificial intelligent Petri net with a best-first search approach is applied to find the proper switching operation decision to solve the problem, in which typical customer load patterns derived from a load survey study are used to determine the daily load profiles of each section of the distribution feeders. In [21], an innovative algorithm for determining the outage contingency of a line leading to a possible system split of a power system is described. Moreover, in [22] corrective switching actions for contingencies with potential violations are proposed for N-1-1 contingencies using a security-constrained unit commitment model that acquires supplementary reserves. A novel algorithm to determine line outage contingencies based on a fast decoupled load flow is examined in [23].

In [24], an extensive reconfiguration review on power distribution network reconfiguration is stated. Different optimization methods are implemented for optimal distribution network reconfiguration. The classical mathematical formulation is presented in [25], [26], [27]. In [25], a multi-objective optimization non-linear problem incorporates these single objectives using weighting multipliers: minimization of power losses, harmonic distortion and voltage dip. In [26], a mixed-integer linear program represent both the service restoration and reconfiguration subproblem improving the service restoration in case of any contingency and minimizing the annual energy losses for different load levels, considering reliability index limits. A mixed-integer second-order programming problem is solved in [27] in which power loss is minimized in the presence of renewable energy. Besides, reconfiguration problems have been studied with heuristic and metaheuristic algorithms. The heuristic techniques used are: artificial bee colony algorithm [28], minimum spanning tree algorithm [29], non-dominated sorting particle swarm optimization [30], binary particle swarm optimization [31], non-dominated sorting genetic algorithm II [32], gravitational search algorithm [33], generalized reduced gradient algorithm and hybrid particle swarm optimization [34] and an interactive fuzzy optimization algorithm based on adaptive particle swarm optimization [35]. In [36], a bio-inspired methaheuristic artificial immune system is developed. In [37], [38] comparisons of the results of the different heuristic methods are presented.

Recently, works have been carried out to deal with the disconnection from the bulk power system operating in an islanding mode. Controlled islanding is an active and effective way of avoiding catastrophic wide area blackouts. In [39], a two-step controlled islanding algorithm that uses spectral clustering to find a suitable islanding solution for preventing the initiation of wide area blackouts by undamped electromechanical oscillations is proposed. In [40], a flexible optimization approach to the problem of intentionally forming islands in a power network is introduced. A mixed-integer linear programming formulation is provided for the problem of simultaneously deciding on the boundaries of the islands and adjustments to generators, so as to minimize the expected load shed while ensuring no system constraints are violated. In [41], a flexible optimization-based framework for intentional islanding is developed in order to split the network while minimizing the amount of load shed and disruption. Reference [42] shows a procedure in which generators and loads can remain connected after islanding to balance the real power of the island, evaluating the feasibility of islanded operation and planning.

In [43], a detailed discussion about various modes of operation, classification, challenges and control issues of islanded microgrids is performed. Additionally, this work also focuses on various control techniques, control issues such as angle droop control and frequency droop control, along with supplementary and adaptive control. In [44], a bi-level integrated planning model of a microgrid is implemented. The upper level co-optimizes the allocation of photovoltaic and energy storage together with network reconfiguration to minimize the total economic cost and, in the lower level the maximization of the expected photovoltaic generation is performed. A comprehensive learning particle swarm optimization is used in [45] to optimally partition the distribution system in case of main upstream loss in order to find the optimal islanding scheme of the distribution system. The objective is to achieve minimum active power generation cost, minimum reactive generation cost and minimum cost of the unserved power while satisfying system operational constraints.

To the best of our knowledge, little attention has been paid to contingency analysis and islanding in distribution systems compared to transmission systems. The difficulty to reconfigure the network allowing for the possibility of having radial islands in distribution systems when evaluating all possible N-1 contingencies shows the need to study these issues. Furthermore, the novelty of our models begins from extending the AC power flow in [46] and integrating wind and storage. Tables 1.1 and 1.2 summarize the contents of the state-of-art works for transmission and distribution systems in comparison to the real-time operation optimization models "Contingency Assessment and Distribution Network Reconfiguration in Distribution Grids Including Wind Power and Energy Storage" (approach 1) and "Islanding in Distribution Systems Considering Wind Power and Storage" (approach 2) proposed in this thesis.

Approach	Contingency Analysis	Reconfiguration	Islanding	Generation	Storage	Stochasticity
[5]	✓	×	×	✓	×	×
[6]	✓	×	×	✓	×	×
[7]	✓	×	✓	✓	×	×
[8]	✓	×	×	✓	×	×
[9]	✓	×	×	✓	×	✓
[11]	✓	×	×	✓	✓	×
[13]	✓	×	✓	✓	×	✓
[14]	✓	✓	✓	✓	×	×
[16]	✓	✓	×	✓	×	×
[17]	✓	×	×	✓	×	×
[22]	✓	✓	×	✓	×	×
[23]	✓	×	✓	✓	×	×
[39]	×	×	✓	✓	×	×
[40]	×	×	✓	✓	×	×
[41]	×	✓	✓	✓	×	×
[42]	×	×	✓	✓	×	×

Table 1.1: Comparison of real-time models for transmission systems.

Approach	Contingency Analysis	Reconfiguration	Islanding	Generation	Storage	Stochasticity
[10]	✓	✓	×	×	×	×
[12]	✓	×	×	✓	✓	×
[15]	✓	×	×	✓	×	×
[18]	×	✓	×	×	×	×
[19]	✓	✓	×	×	×	×
[20]	✓	×	×	✓	✓	×
[21]	✓	×	✓	✓	×	×
[24]	×	✓	×	✓	×	✓
[25]	×	✓	×	✓	×	×
[26]	✓	×	×	✓	×	×
[27]	✓	×	×	✓	×	✓
[28]	×	✓	×	✓	×	×
[29]	×	✓	×	×	×	×
[30]	×	✓	×	✓	×	×
[31]	✓	✓	×	✓	×	×
[32]	×	✓	✓	✓	×	✓
[33]	×	✓	×	✓	×	✓
[34]	×	✓	×	✓	✓	×
[35]	×	✓	×	✓	✓	✓
[36]	×	✓	×	✓	×	✓
[37]	×	✓	×	×	×	✓
[38]	×	✓	×	✓	×	×
[43]	×	×	✓	✓	×	×
[44]	✓	×	✓	✓	×	✓
[45]	×	×	✓	✓	×	×
[46]	×	✓	×	✓	×	×
(approach 1)	✓	✓	✓	✓	✓	✓
(approach 2)	×	✓	✓	✓	✓	✓

Table 1.2: Comparison of real-time models for distribution systems.

1.5.2 Optimal placement models

The aim of the optimal placement of both DG and ESS is to provide the best locations and sizes of DG and ESS to optimize electrical distribution network operation and planning. Several models and methods have recently been suggested for the solution of the optimal DG placement. In [47], an overview of state-of-the art methods and models applied to these problems, classifying and analyzing the current and future research trends in this field is presented. Additionally, a summary of the existent approaches has been made considering the minimization of power losses, enhancement of voltage stability and improvement of voltage profile, as in [48].

Some models use exact optimization techniques such as deterministic mixed-integer nonlinear programming [49], stochastic mixed-integer nonlinear programming [50], deterministic mixed-integer linear programming [51], stochastic mixed-integer linear programming [52], linear bi-level programming [53], non-linear programming [54], [55] and mixed-integer second-order cone programming [56] for optimal placement. Other works use hybrid optimization model [57], genetic algorithms [58], [59], [60], particle swarm optimization [61], differential evolution algorithms [62] and other heuristic methods [63], [64].

In [49], the goal is to improve the voltage stability margin while proposing a method of locating and sizing DG units. The work in [50] refers to a novel and comprehensive solution methodology for optimum allocation of different wind turbine types minimizing the weighted sum of active power losses and system reliability indexes. In [51], the objective is to minimize the total cost (conventional generation and storage operating costs) for the management of the transmission system with storage. A bi-level energy storage programming configuration model for energy storage capacity and location configuration is implemented in [53]. For the upper-level optimization, a depth search method is applied to obtain the optimal placement of ESS. For the lower-level optimization, the optimal capacity of ESS is solved to meet system reliability requirements. In [54], a two-stage iterative process is followed to minimize overall capital cost in which the first stage uses a multi-period AC optimal power flow to obtain initial storage sizes considering hourly wind and load profiles. The second stage examines the actual curtailment level to be achieved by the storage sizes determined in the first stage. An improved analytical method is proposed in [55] based on some analytical expressions to calculate the optimal size of four different DG types and a methodology to identify the best location for DG allocation. Besides, [56] proposes both a unit commitment and an AC optimal power flow combined together over a sequential time series to find the optimal location and size of ESS. The objective function comprises generation cost, unit start-up/shut-down cost, round trip efficiency loss cost and daily operation cost of ESS. The method in [52] takes a centralized perspective where the objective is to minimize the sum of the expected operating cost and the investment cost of energy storage in addition to annual interruption costs. Reference [57] examines a viable and optimal solution including the sum of the annualized capital, replacement, maintenance and fuel costs for the island of Kavaratti. A comprehensive planning framework is introduced in [58]

to achieve the most effective siting and sizing of ESS that maximizes its benefits in distribution networks. In [59], the objective function minimizes the total cost comprising the annual installation and maintenance costs of the ESS units in addition to annual interruption costs. Reference [60] presents a distribution system reconfiguration model that considers the network configuration effect and the optimal DG allocation and sizing to obtain an optimal condition for a distribution network based on operational and reliability improvements. Furthermore, in [61] the best location for the installation of ESS and the best possible operation schedules for ESS and power plants is done to achieve the minimum ESS operation cost. Moreover, a stochastic planning framework is proposed in [62] to minimize the investment and operation costs. The uncertainties in wind power and load are modeled by MC simulation, and a chance-constrained stochastic optimization model is formulated to determine the location and capacity of ESS while ensuring wind power utilisation level. The work in [63] describes a heuristic method to find the optimal location and capacity of ESS including transmission and distribution networks, and reducing the generation and ESS operation costs. Finally, the minimization of the distribution feeder active power loss as well as energy loss is presented in [64]. In this work, the optimization technique is based on a modification of the traditional big bang-big crunch method for the optimal placement and sizing of voltage-controlled distributed generators.

Table 1.3 summarizes the contents of the state-of-art works for the optimal location models in comparison to the approach developed in "Optimal Placement of Energy Storage and Wind Power under Uncertainty" regarding the time horizon used, the location of the units and whether the model is stochastic or not.

Approach	ESS location	RES location	Stochasticity	Time horizon
[49]	×	✓	×	1 instant
[50]	×	×	✓	1 year
[51]	✓	×	×	1 month
[52]	✓	×	✓	10 years
[53]	✓	×	×	1 year
[54]	✓	×	×	24 hours
[55]	×	✓	×	1 instant
[56]	✓	×	×	24 hours
[57]	✓	✓	×	25 years
[58]	✓	×	✓	multi-year
[59]	✓	×	✓	1 year
[60]	×	✓	×	1 year
[61]	✓	×	×	24 hours
[62]	✓	×	✓	24 hours
[63]	✓	×	×	24 hours
[64]	×	✓	×	24 hours
Our approach	✓	✓	✓	1 week

Table 1.3: Comparison of optimal location models.

1.5.3 Expansion planning models

In recent years, new models have been applied to the traditional electric power system expansion planning including new resources such as RES, ESS and EV. The state-of-art of the expansion planning models is shown in Table 1.4.

Conventional planning models have solved the optimal expansion of distribution assets with the replacement and addition of feeders, the reinforcement of existing substations and the construction of new substations as in [65]. In [66], a review of the state-of-art works of distribution expansion planning problems is presented. A new approach has been developed in [67] for simultaneous distribution, sub-transmission, and transmission network expansion planning. In this work, an optimization problem has been formulated where an improved genetic algorithm is used to solve such a complex problem. In [68], a multi-objective framework for primary distribution system planning is solved incorporating probabilistic customer choices in reliability. The work in [69] includes generation expansion planning in addition to the traditional distribution expansion planning models. It is a multistage stochastic investment model with thermal and wind generation assets. The work in [70] proposes a multi-year expansion planning method for both the distribution network and DG units method to enable distribution systems to support the growing penetration of plug-in EV. A multistage long-term expansion planning problem of EDS is developed in [71], considering the increasing capacity of existing substations, construction of new substations, allocation of capacitor banks and/or voltage regulators, and construction and/or reinforment of circuits. It considers the presence of DG, however, the method does not allocate new sources. A multi-year expansion planning in distribution networks is proposed in [72] in which the optimal expansion scheme of the distribution network includes the reinforcement pattern of primary feeders as well as the location and size of DG. In [73], a tri-level reliability-constrained robust expansion planning framework is implemented modeling the uncertainty of electricity demand, wind power generation and availability of units and lines. In [74], an optimal smart distribution grid multistage expansion planning is presented, in which reinforcement or installation time, capacity and location of MV substations and DG are taken into consideration. The optimal reinforcement of existing lines and substations, the installation of new ones, the investment on renewable and non-renewable DG is studied in [75]. A dynamic model for distribution system expansion planning is presented in [76] considering DG. It determines the optimal location and size of DG as well as the reinforcement strategy for distribution feeders. In [77], [78], load level duration curves are introduced allowing the incorporation of chronological information minimizing the loss of information of the sequence between hours. In [77], a stochastic-programming-based model driven by the minimization of the expected investment and operational costs of new and existing feeders, new and existing substations and DG is developed.

Other works have studied the operational planning of ESS. A novel model in [78] proposes to accurately include demand response and ESS in the joint distribution network and generation expansion planning. In [79], the optimal operation planning of batteries in distribution networks is performed by metaheuristic methods using probabilistic variation of the inputs using the point estimation

method for the optimal planning of batteries. In [80], a multistage expansion planning model for replacing and adding circuits is performed, in which typical daily scenarios are assessed for the hourly economic dispatch of ESS. In [81], the proposed planning methodology is a novel four-layer procedure that considers the uncertainty of battery characteristics as well as load and wind power. The long-term planning layer optimizes the location, capacity and power rating of batteries. In [82], the optimal planning determines the location, capacity and power rating of batteries while minimizing the cost objective function subject to technical constraints. A multistage active distribution network planning model that is integrated with the application of ESS is presented in [83]. The long-term expansion planning decisions include those for replacing and adding circuits and introducing ESS. The work in [84] aims to minimize the investment and operation of lines and ESS costs over the planning horizon.

Moreover, some works include the existence of EV loads in the joint distribution, generation and ESS expansion planning without including the installation cost of EVCS. In [85], a non-parametric chance-constrained optimization to invest in ESS units is proposed, in which the uncertainties of DG and EV, are considered using the probability density function. In [86], a multi-objective optimal planning of battery energy storage and DG units in an active distribution network is presented, in which the power profile of EV is modeled by fuzzy values. Very recently, more attention has been paid to the optimal planning of EVCS. In [87], the optimal planning of EVCS in distribution systems is developed with the minimization of total costs. In [88], a multi-objective planning model of a distribution network containing DG and EVCS is implemented. A scenario expansion planning for distribution systems is proposed in [89] considering the integration of EV, with dumb charging and coordinated charging modes. The research in [90] deals with the joint planning of distribution networks including distributed energy storage systems and electric vehicle charging stations that meet the demand of electric vehicle charging load. Finally, regarding the classification of the optimization models, exact optimization techniques are used for deterministic mixed-integer linear programs as in [71], [80], [83], stochastic mixed-integer linear programing [69], [77], [78], bi-level programming [90], chance-constrained optimization [85], tri-level decomposition algorithm [73] and a primal-dual interior point algorithm [87]. On the other hand, heuristic techniques are used, such as genetic algorithms [67], [68], [89], [70] combined with tabu search [65], particle swarm optimization [89], hybrid simulated annealing algorithms combined with tabu search [86], hybrid particle swarm optimization and tabu search [79], [82] hybrid simulated annealing and genetic algorithm [81], group search optimization algorithms [74], evolutionary algorithms [75], [88], new evolutionary algorithm-based solution methods called binary chaotic shark smell [72], hybrid modified integer-coded harmony search, and enhanced gravitational search algorithms [76].

1.5.4 Reliability assessment models

The main objective of electrical power systems is to provide reliable and economical electricity to customers. Thus, reliability assessment must be studied including

Approach	Network Investment	RES Investment	ESS Investment	EVCS Investment	Stochasticity
[65]	✓	×	×	×	×
[67]	✓	×	×	×	×
[68]	✓	×	×	×	✓
[69]	×	✓	×	×	✓
[70]	✓	✓	×	×	✓
[71]	✓	✓	×	×	×
[72]	✓	✓	×	×	×
[73]	✓	✓	×	×	✓
[74]	✓	✓	×	×	×
[75]	✓	✓	×	×	✓
[76]	✓	✓	×	×	✓
[77]	✓	✓	×	×	✓
[78]	✓	✓	✓	×	✓
[79]	×	×	✓	×	✓
[80]	✓	×	×	×	×
[81]	×	×	✓	×	✓
[82]	×	×	✓	×	✓
[83]	✓	×	✓	×	×
[84]	✓	×	✓	×	×
[85]	×	×	✓	×	✓
[86]	×	✓	✓	×	✓
[87]	×	×	×	✓	×
[88]	✓	✓	×	✓	×
[89]	×	✓	✓	×	✓
[90]	×	×	✓	✓	×
Our approach	✓	✓	✓	✓	✓

Table 1.4: Comparison of investment decision planning models.

a number of practices emerging in the smart grid recent context. Classical reliability analysis of distribution systems is based on the calculation of a number of indicators taking into account the frequency and duration of the interruptions leading to the determination of the non-supplied energy.

Reliability indicators may be calculated either a *posteriori* (at the end of the year) or a *priori* (expected behaviour of the network) in order to be used as objective functions for single- or multi-objective optimization purposes [91] or within operational planning [92], [93] or expansion planning tools [94]. In the classical a priori reliability analysis, predictive methods based on historical data forecast the future continuity levels. Both deterministic or probabilistic methods can be used.

Analytical methods or MC methods may be used for probabilistic reliability analysis as in [95], however, analytical methods are faster [96]. A novel method for computing the probability distribution using the characteristic functions is illustrated in [97].

In [98], a continuous-time Markov-chain-based analytical approach is performed. A limitation of the analytical approach is that it cannot consider common-modes to interfere near-coincident faults. An analytical formulation of reliability assessment with remote-controlled switches and islanded microgrids is presented in [99]. An analytical method that considers the DG reliability model, islanding operation and changes in the protection strategy is described in [100]. On the other hand, MC methods [95] can include the effects of multiple faults, as well as dependencies on external variables and time-changing loads or generation. Different types of MC simulation include non-sequential methods with state sampling or state transition sampling [101], pseudo-sequential MC methods with a non-sequential selection of the failure states and a sequential simulation of the sequence of neighboring states [102]. A recent proposal to represent correlated time series within a non-sequential method is discussed in [103]. A non-sequential MC method is used in [104] to evaluate the reliability of active distribution grids. The application of a pseudo-sequential MC method is discussed in [105]. MC sequential simulation methods are also used in [106]. In [107], a set of methodologies to assess the reliability of power distribution network with the penetrations of battery energy storage systems and intermittent distribution sources is proposed. First, an analytic approach based on Markov models is applied for assessing the reliability analysis in distribution systems. Then the method is verified by a sequential MC simulation method and extended to a more complex distribution system. Reliability analysis techniques can be detailed by introducing the variation of the load patterns throughout time [108]. Hourly patterns of load and RES are used in the analytical approach presented in [109].

The penetration of RES, ESS, EV and demand response has raised interest in reliability assessment, in particular with respect to the possibility of creating islands during the service restoration process. In [110], EV operating in a vehicle-to-grid mode are considered as a further possibility of enhancing reliability by exploiting the local supply located in parking lots. Centralized and dispersed contributions of electric vehicles including vehicle to grid and vehicle-to-home are addressed in [111].

The availability of a mobile emergency power supply with generation and storage resources has to be properly coordinated in order to obtain the greatest benefits from these resources. The solution strategies must also take into account the importance given to the network nodes. The pre-positioning of truck-mounted mobile emergency generators is proposed in [112] to dispatch these generators to some nodes of the distribution system with the aim of restoring critical loads, by forming multiple microgrids.

1.6 Organization of the Thesis

The thesis entitled **"Operation and Planning Models in Future Distribution Systems with Renewable Energy, Generic Energy Storage and Electric Vehicles"** has been developed following the Compendium of Papers format in which the most relevant ones are 5 journal papers published in the following journals: *IEEE Transactions on Sustainable Energy*; *Sustainable Energy, Grids and Networks*; *Energies*; *IEEE Transactions on Smart Grid* and *IEEE Transactions on Industry Applications.*

The thesis is divided into 8 chapters:

Chapter 1 The first chapter describes the motivation, objectives, hypotheses, methodology and the sequence of tasks for the development of the research works presented in this thesis. Finally, a literature review is shown for each of the research topics dealt with in this thesis.

Chapter 2 This chapter presents an N-1 contingency analysis tool and optimal reconfiguration for the distribution network, allowing for islanded operation by maintaining each subsystem radially operated. All network operating costs, renewable energy curtailment cost and the energy storage operation costs are optimized. This work has been published in *IEEE Transactions on Sustainable Energy.*

P. Meneses de Quevedo, J. Contreras, M.J. Rider and J. Allahdadian, "Contingency Assessment and Network Reconfiguration in Distribution Grids Including Wind Power and Energy Storage," IEEE Transactions on Sustainable Energy, vol. 6, no. 4, pp. 1524–1533, Oct. 2015: ©2015 IEEE. Reprinted, with permission, from [P. Meneses de Quevedo, J. Contreras, M.J. Rider and J. Allahdadian, "Contingency Assessment and Network Reconfiguration in Distribution Grids Including Wind Power and Energy Storage," IEEE Transactions on Sustainable Energy, vol. 6, no. 4, pp. 1524–1533, Oct. 2015].

Chapter 3 This chapter presents the work published in *Sustainable Energy, Grids and Networks.* An algorithm to have the islanded area energized avoiding a complete blackout is developed. The model is capable of managing the network mantaining the load and generation units on-line. The work shows how the combination of RES and ESS is desirable to improve reliability. Different levels of power for wind generation and demand are analyzed in this research in order to show the islanded power balance.

Chapter 4 A probabilistic model based on mixed-integer linear programming is presented with the aim of locating both a wind power generator and an energy storage system, minimizing all the costs associated with the operation of the distribution network. Different installed amounts of wind and ESS capacities are analyzed emphasizing the fact that ESS avoid wind curtailment and its associated cost. This work has been published in *Energies*.

Chapter 5 The proposed multi-stage multi-objective model for the joint expansion planning of generation and distribution networks has the objective of minimizing the investment and operational costs. Renewable energy, ESS and EVCS are considered in the expansion planning model. The work analyzes the benefits derived from the investment in ESS further emphasized with the presence of EV. This work has been accepted in *IEEE Transactions on Smart Grid*.

P. Meneses de Quevedo, G. Muñoz-Delgado and J. Contreras, "Impact of Electric Vehicles on the Expansion Planning of Distribution Systems considering Renewable Energy, Storage and Charging Stations," in IEEE Transactions on Smart Grid (accepted): ©2015 IEEE. Reprinted, with permission, from [P. Meneses de Quevedo, G. Muñoz-Delgado and J. Contreras, "Impact of Electric Vehicles on the Expansion Planning of Distribution Systems considering Renewable Energy, Storage and Charging Stations," in IEEE Transactions on Smart Grid (accepted)].

Chapter 6 This chapter deals with the reliability assessment for distribution system applications in which a sequential MC method has been implemented. The use of this method includes emerging practices in the smart grid context comprising conventional demand profiles for different types of consumers, several approaches to calculate ENS, intraday reconfiguration strategies and the exploitation of dedicated solutions with RES and mobile generation. This work has been accepted in *IEEE Transactions on Industry Applications*.

P. Meneses de Quevedo, J. Contreras, A. Mazza, G. Chicco and R. Porumb, "Reliability Assessment of Microgrids with Local and Mobile Generation, Time-Dependent Profiles, and Intra-Day Reconfiguration," in IEEE Transactions on Industry Applications, (accepted): ©2015 IEEE. Reprinted, with permission, from [P. Meneses de Quevedo, J. Contreras, A. Mazza, G. Chicco and R. Porumb, "Reliability Assessment of Microgrids with Local and Mobile Generation, Time-Dependent Profiles, and Intra-Day Reconfiguration," in IEEE Transactions on Industry Applications, (accepted)].

Chapter 7 This chapter presents a summary of the thesis, the main conclusions, the achievements obtained and suggestions for future work.

Chapter 8 Finally, a Spanish language version of the conclusions is presented.

Chapter 2

Contingency Assessment and Network Reconfiguration in Distribution Grids Including Wind Power and Energy Storage

Contingency Assessment and Network Reconfiguration in Distribution Grids Including Wind Power and Energy Storage

Pilar Meneses de Quevedo, Javier Contreras, *Fellow, IEEE*, Marcos J. Rider, *Member, IEEE*, and Javad Allahdadian

***Abstract*—In case of abnormal conditions, distribution systems should be reconfigured to overcome the impacts of outages such as overloads of network components and increased power losses. For this purpose, energy storage systems (ESS) and renewable energy sources (RES) can be applied to improve operating conditions. An optimal contingency assessment model using two-stage stochastic linear programming including wind power generation and a generic ESS is presented. The optimization model is applied to find the best radial topology by determining the best switching sequence to solve contingencies. The proposed model is applied to a 69-node distribution system and the results of all possible contingencies in the network are examined considering three different case studies with several scenarios. In addition, a reconfiguration analysis including all the contingencies is presented for the case studies.**

***Index Terms*—Contingency analysis (CA), distributed generation (DG), islanding, optimal power flow, stochastic programming, storage devices.**

NOTATION

Indexes:

i, j, k	Node index.
r	Block index of linearization.
t	Real-time period index on a 10-min basis.
ω	Scenario index.

Parameters:

C^{sw}	Switching cost (\$).
C^{loss}	Real power losses cost (\$/MWh).
C^{w_curt}	Wind curtailment cost (\$/MWh).
C^{d_curt}	Real power demand curtailment cost (\$/MWh).
C^{sub}	Cost of real power from substation (\$/MWh).
C^{sp}	Production scheduled cost (\$/MWh).
C^{ss}	Storage scheduled cost (\$/MWh).
C^{rp}	Production scheduled reserve cost (\$/MWh).
C^{rs}	Storage scheduled reserve cost (\$/MWh).
$\hat{C}^{\text{rs}}$	Real-time energy storage cost (\$/MWh).
$\hat{C}^{\text{rp}}$	Real-time energy production cost (\$/MWh).
C_{ij}	State of a contingency in branch *ij*.
$d_{it\omega}$	Real power demand at node i (MW).
$q_{it\omega}$	Reactive power demand at node i (MVAr).
ini_{ij}	Initial state of a switch in branch *ij*.
$\overline{I}_{ij}$	Maximum current flow in branch *ij* (A).
$m_{ijrt\omega}$	Slope of the rth block for branch *ij*.
N_{loop}	Number of switches in a loop.
PF_i	Power factor (PF) of the load at node i.
$P^{\text{fore}}_{it\omega}$	Wind real power forecast at node i (MW).
R^{tot}	Total number of blocks in the piecewise linearization.
$\underline{s}^s_i, \overline{s}^s_i$	Minimum/maximum power storage at node I (MW).
$\underline{s}^p_i, \overline{s}^p_i$	Minimum/maximum production at node i (MW).
R_{ij}	Resistance of branch *ij* (Ω).
X_{ij}	Reactance of branch *ij* (Ω).
Z_{ij}	Impedance of branch *ij* (Ω).
V_{nom}	Nominal voltage of the distribution network (kV).
$\underline{V}_i, \overline{V}_i$	Minimum/maximum voltage at node i (kV).
$\overline{W}$	Upper bound of variable $W_{ijt\omega}$ (kV).
x^s_{i0}	Initial energy level of storage unit at node i (MWh).
$\underline{x}_i, \overline{x}_i$	Min/max storage capacity at node i (MWh).
η^s_i, η^p_i	Efficiency storage/production rates.
$\Delta S_{ijrt\omega}$	Upper bound for the rth block of the power flow through branch *ij*.
Δ	Real-time period (10 min) (h).

Nonnegative variables:

$I^2_{ijt\omega}$	Square of the current flow of branch *ij* (A^2).
$P^{\text{wind}}_{it\omega}$	Real power wind generation at node i (MW).
$P^{w\_\text{curt}}_{it\omega}$	Real power wind curtailment at node i (MW).
$P^{d_{\text{curt}}}_{it\omega}$	Real power demand curtailment at node i (MW).
$P^2_{ijt\omega}$	Square of the real power in branch *ij* (MW^2).
$Q^2_{ijt\omega}$	Square of the reactive power in branch *ij* (MVAr^2).
$P^+_{ijt\omega}$	Real power flow in branch *ij*, downstream (MW).
$P^-_{ijt\omega}$	Real power flow in branch *ij*, upstream (MW).
$Q^+_{ijt\omega}$	Reactive power flow (downstream) (MVAr).
$Q^-_{ijt\omega}$	Reactive power flow (upstream) (MVAr).
r^p_i, r^s_i	Scheduled power production/storage reserve (MW).

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$\hat{r}^p_{it\omega}$, $\hat{r}^s_{it\omega}$	Real-time production/storage reserve (MW).
s^p_i, s^s_i	Scheduled power production/storage (MW).
$V^2_{it\omega}$	Square of the voltage magnitude at node i (kV^2).
$W^2_{ijt\omega}$	Square of the voltage drop for branch *ij* (kV^2).
$\hat{x}_{it\omega}$	Storage level at node i (MWh).
$\Delta P_{ijrt\omega}$	Value of the rth block of real power (MW).
$\Delta Q_{ijrt\omega}$	Value of the rth block of reactive power (MVAr).

Free variables:

$P^{\text{sub}}_{it\omega}$	Real power of a substation at node i (MW).
$Q^{\text{sub}}_{it\omega}$	Reactive power of a substation at node i (MVAr).
$Q^{\text{wind}}_{it\omega}$	Reactive power of wind generation at node i (MVAr).
$Q^{d_{\text{curt}}}_{it\omega}$	Demand reactive power curtailment (MVAr).

Binary variables:

$v^{P+}_{ijt\omega}$	Variable related to real power (upstream).
$v^{P-}_{ijt\omega}$	Variable related to real power (downstream).
$v^{Q+}_{ijt\omega}$	Variable related to reactive power (upstream).
$v^{Q-}_{ijt\omega}$	Variable related to reactive power (downstream).
v^s_{it}, v^p_{it}	Variables related to storage or production.
y_{ij}	State of the switch in branch *ij*.

I. Introduction

CONTINGENCY analysis (CA) provides tools to study contingencies in electrical networks and analyze their behavior in case of outages in one of the electrical components such as lines, transformers, and generators. Several studies have been carried out to assess contingencies in electrical networks. The comparison of some techniques such as ranking, screening, bounding, and fast power flow techniques has been done in [1] and [2]. Methods such as genetic algorithms [3], [4], bi-level programming [5], and other new power flow calculation approaches [6] have been developed to solve CA problems. Likewise, in terms of behavior assessment of power networks, some works have been presented to evaluate voltage security [7], [8], operation of transmission networks [9], [10], and optimal switching under $N-1$ contingencies [11]–[13].

Moreover, reconfiguration of distribution systems (RDS) aims at finding the best topology of the system concerning power losses, energy demand, and operational performance. In general, two major groups of optimization methods have been represented to solve the RDS problem: 1) exact techniques and 2) heuristic and metaheuristic techniques. In literature, exact techniques such as branch and bound are only used to solve relaxed models [14]–[18]. On the contrary, heuristic and metaheuristic methods such as ant colony [19], [20], genetic algorithms [21]–[23], and particle swarm optimization [24] have been applied for complete models.

In particular, RDS can be used to improve the operation of distribution systems in case of contingencies, considering renewable energy sources (RES) and energy storage systems (ESS) in electrical networks. Although the availability of RES and ESS can be seen as an opportunity to exploit available resources near loads and compensate energy demand, problems may arise due to the intermittency and uncertainty of RES [4], [25] and the integration of ESS into electrical distribution systems (EDS) [26], [27].

A mixed integer linear programming (MILP) reconfiguration model under an $N-1$ reliability criterion using stochastic programming considering wind energy and ESS in EDS is introduced. The steady-state operation of a radial EDS is complicated to model linearly; hence, an alternative current (ac) flow is approximated through linear expressions. The proposed model also includes switching operation, intermittent RES, and generic ESS. The analysis of $N-1$ contingencies is performed using a contingency parameter per branch to locate the fault in the branch.

Due to several technical reasons such as low cost operation, simplicity of analysis and coordination, and reduction of short circuit current, EDS must operate with a radial topology (even with a meshed structure). In addition, MILP is applied, in this paper, due to the following advantages: 1) the mathematical model is robust; 2) the computational behavior of a linear solver is more efficient than nonlinear solvers; and 3) using classical optimization techniques, convergence can be guaranteed.

The main contributions of this paper are as follows.

1) Regarding the methodology, a two-stage stochastic mathematical MILP for contingency response is introduced to consider the inconsistency and intermittency of the renewable power sources.
2) From a modeling perspective, a joint programming model of the optimal reconfiguration and contingency evaluation is presented here for a distribution system. However, in the literature, optimal switching under contingency conditions is reported only for transmission networks [11]–[13].
3) The benefits of combining RES with ESS in distribution networks, especially under contingencies and abnormal conditions, are analyzed.

Another relevant aspect of the presented optimization model is the minimization of the overall operation costs, including switching and demand and wind curtailment costs. Note that the problem formulation assumes that the overall investment costs have already been minimized in a previous planning phase where the best locations for wind and storage have been selected in advance.

This paper is organized as follows. Section II describes the mathematical formulation of generation and storage models. Section III defines the mathematical model as a stochastic MILP. The main results of the case studies considering contingencies and reconfigurations are shown in Section IV. Finally, conclusion is presented in Section V.

II. Storage Modeling

In modern power systems, storage devices have grown rapidly. ESSs are integrated into EDS to consider several purposes such as meeting real-time power demand, smoothing output power of RES, improving power system reliability,

and being economically efficient [28]. Thus, a generic storage system is modeled as follows:

$$\underline{s}_i^s \le s_i^s + r_i^s \le \overline{s}_i^s v_{it}^s \tag{1}$$

$$\underline{s}_i^p \le s_i^p + r_i^p \le \overline{s}_i^p v_{it}^p \tag{2}$$

$$0 \le \hat{r}_{it\omega}^p \le r_i^p \tag{3}$$

$$0 \le \hat{r}_{it\omega}^s \le r_i^s \tag{4}$$

$$\underline{x}_i \le \hat{x}_{it\omega} \le \overline{x}_i \tag{5}$$

$$\hat{x}_{it\omega} = \hat{x}_{it-1\omega} + \Delta\left[\eta_i^s s_i^s - \left(1/\eta_i^p\right) s_i^p\right] + \Delta\left[\eta_i^s \hat{r}_{it\omega}^s - \left(1/\eta_i^p\right) \hat{r}_{it\omega}^p\right] \tag{6}$$

$$\hat{x}_{it=0\omega} = x_0^s \tag{7}$$

$$v_{it}^p + v_{it}^s \le 1. \tag{8}$$

The minimum and maximum storage limits (charge) and productions (injection into the network) are defined in (1) and (2). It is worth noting that s_i^s and s_i^p are implemented in these equations to smooth the output power of the storage unit and r_i^s/r_i^p to guarantee that real-time power balance is within the storage capacity. In (3) and (4), the actual real-time reserves are confined to the maximum reserve bounds r_i^s/r_i^p. The upper and lower bounds of energy capacity in storage units are defined by (5). The ESS transition function is represented by (6). Equation (7) limits the remaining energy in the storage unit. Finally, in (8), binary variables v_{it}^p and v_{it}^s are defined and added to (1) and (2) to avoid producing and storing energy simultaneously.

III. Stochastic Formulation of Contingency Assessment and Network Reconfiguration

The following assumptions are defined to represent the simplified operation of EDS including switches, generation, and storage devices.

1) The load pattern in EDS is altered every 10 min.
2) EDS are balanced three-phase systems and can be represented by an equivalent single-phase circuit.
3) Storage energy losses are ignored.
4) Storage and production of energy occur at constant power in storage units during real-time periods (10 min).
5) The location of storage units has already been defined in the planning phase.
6) Wind turbines are located at nodes with high demand.
7) The maximum contingency duration is 1 h, considering wind scenarios, which is divided into 10-min periods (six periods).
8) Faults are considered in feeders and circuit breakers.
9) Islanded radial operation of the system is possible with distributed generation (DG) integration.

To distinguish the direction (sense) of the current and power flow (forward or backward), two positive separate variables are shown in Fig. 1.

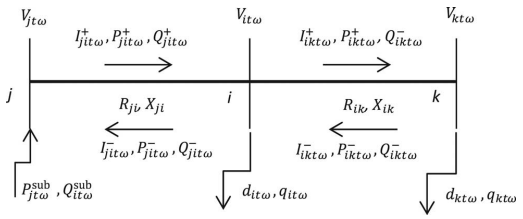

Fig. 1. Illustrative radial distribution system.

A. Objective Function

The objective function is formulated through two-stage stochastic programming as shown in (9)–(13). At the first stage, regardless of scenarios, i.e., only considering contingency conditions, the cost of opening and closing switches and the scheduling of storage units are assigned. At the second stage, the expected values of the total cost of power losses in the network, the cost of real-time production/storage of the storage units, and the cost of curtailment of both generation and demand, with respect to different scenarios and contingency conditions, are assigned. At the first stage, the variables are only related to contingency conditions and variables are relevant to both contingencies and scenarios at the second stage.

Objective function:

$$\min \phi + \gamma + E\left[\psi\left(\omega\right)\right] + E\left[K\left(\omega\right)\right] \tag{9}$$

where the first stage is given by $\phi + \gamma$:

1) Switching cost

$$\phi = \sum_{\substack{ij \\ \text{ini}_{ij}=0}} y_{ij} C^{\text{sw}} + \sum_{\substack{ij \\ \text{ini}_{ij}=1}} \left(1 - y_{ij}\right) C^{\text{sw}}. \tag{10}$$

2) Scheduled production/storage cost function

$$\gamma = \sum\nolimits_i \left[s_i^s C^{\text{ss}} + s_i^p C^{\text{sp}} + r_i^s C^{\text{rs}} + r_i^p C^{\text{rp}}\right]. \tag{11}$$

Next, the second stage is given by $\psi\left(\omega\right) + K\left(\omega\right)$:

1) Network costs (losses and substation costs)

$$\psi\left(\omega\right) = \Delta\left[\sum\nolimits_t \sum\nolimits_{ij} R_{ij} I_{ijt\omega}^2 C^{\text{loss}} + \sum\nolimits_t \sum\nolimits_i P_{it\omega}^{\text{sub}} C^{\text{sub}}\right]. \tag{12}$$

2) Corrective action costs (curtailment and real-time production/storage costs)

$$K\left(\omega\right) = \Delta\left[\sum\nolimits_t \sum\nolimits_i \left(P_{it\omega}^{w\_\text{curt}} C^{w\_\text{curt}} + P_{it\omega}^{d\_\text{curt}} C^{d\_\text{curt}} + \hat{r}_{it\omega}^p \hat{C}^{\text{rp}} + \hat{r}_{it\omega}^s \hat{C}^{\text{rs}}\right)\right]. \tag{13}$$

B. Constraints

The above objective function is subject to a set of constraints to assure optimal operational conditions.

1) Real-Time Power Balance Equations: Real power of wind including curtailment is represented in (14)

$$P_{it\omega}^{\text{wind}} = P_{it\omega}^{\text{fore}} - P_{it\omega}^{w_{\text{curt}}}. \tag{14}$$

Equations (15) and (16) represent the real and reactive power balances at node i, respectively (see Fig. 1). For both active and reactive power, wind power generation, scheduled production/storage, real-time production/storage power of ESS, the power flow from/to the substation, and power demand curtailment are considered. In addition, wind generation curtailment has already been formulated in (14)

$$\begin{aligned} P_{it\omega}^{\text{wind}} &+ \sum\nolimits_j \left(P_{jit\omega}^{+} - P_{jit\omega}^{-}\right) - \sum\nolimits_k \left[\left(P_{ikt\omega}^{+} - P_{ikt\omega}^{-}\right)\right. \\ &\left. + R_{ij} I_{ijt\omega}^2\right] + P_{it\omega}^{\text{sub}} + \left(\hat{r}_{it\omega}^{p} - \hat{r}_{it\omega}^{s}\right) + \left(s_i^p - s_i^s\right) \\ &= d_{it\omega} - P_{it\omega}^{d_{\text{curt}}} \end{aligned} \tag{15}$$

$$\begin{aligned} Q_{it\omega}^{\text{wind}} &+ \sum\nolimits_j \left(Q_{jit\omega}^{+} - Q_{jit\omega}^{-}\right) \\ &- \sum\nolimits_k \left[\left(Q_{ikt\omega}^{+} - Q_{ikt\omega}^{-}\right) + X_{ij} I_{ijt\omega}^2\right] + Q_{it\omega}^{\text{sub}} \\ &= q_{it\omega} - Q_{it\omega}^{d_{\text{curt}}}. \end{aligned} \tag{16}$$

2) Load PF: The following constraint is considered to keep the initial load PF:

$$Q_{it\omega}^{d_{\text{curt}}} = P_{it\omega}^{d_{\text{curt}}} * \left(\tan\left(\arccos\left(\text{PF}_i\right)\right)\right). \tag{17}$$

3) Voltage Drop Equations: The square value of the voltage drop between nodes is represented in (18) as an auxiliary variable $W_{ijt\omega}^2$, which is related to switching operations and contingencies

$$\begin{aligned} V_{it\omega}^2 &- 2\left(R_{ij}\left(P_{ijt\omega}^{+} - P_{ijt\omega}^{-}\right) + X_{ij}\left(Q_{ijt\omega}^{+} - Q_{ijt\omega}^{-}\right)\right) \\ &- Z_{ij}^2 I_{ijt\omega}^2 - V_{jt\omega}^2 + W_{ijt\omega}^2 = 0. \end{aligned} \tag{18}$$

The upper and lower bounds of the square of the voltage deviation for node i are defined by (19)

$$\underline{V}^2 \le V_{it\omega}^2 \le \overline{V}^2. \tag{19}$$

In constraints (20) and (21), $W_{ijt\omega}^2 = 0$ in case of operation of branch *ij* ($C_{ij} = 1$) or switch closure ($y_{ij} = 1$). To satisfy constraints (15) and (16), a proper value for parameter $\overline{W}^2$ should be set to give a sufficient degree of freedom for $W_{ijt\omega}^2$

$$W_{ijt\omega}^2 \ge -\bar{W}^2\left(1 - y_{ij}\right)\left(1 - C_{ij}\right) \tag{20}$$

$$W_{ijt\omega}^2 \le \bar{W}^2\left(1 - y_{ij}\right)\left(1 - C_{ij}\right) \tag{21}$$

4) Nonlinear Apparent Power Equation: The current flow magnitude calculation is represented by nonlinear constraint (22), where both sides of the constraint are linearized as explained in Section III-D

$$V_{jt\omega}^2 I_{ijt\omega}^2 = P_{ijt\omega}^2 + Q_{ijt\omega}^2. \tag{22}$$

5) Current and Power Magnitude Limits: Due to thermal limits in EDS, a set of constraints is introduced for current, real power, and reactive power in (23), (24)–(25), and (26)–(27), respectively. In addition, $v_{ijt\omega}^{P+}$, $v_{ijt\omega}^{P-}$, $v_{ijt\omega}^{Q+}$, and $v_{ijt\omega}^{Q-}$ are binary variables to avoid considering forward and backward power flows simultaneously. The constraints (23)–(27) define the limits through switching devices in branches if they are closed; otherwise, all magnitudes are equal to zero. Note that (24)–(27) are auxiliary constraints to improve the convergence of the proposed model

$$0 \le I_{ijt\omega}^2 \le \overline{I}_{ij}^2 C_{ij} y_{ij} \tag{23}$$

$$P_{ijt\omega}^{+} \le V_{\text{nom}} \overline{I}_{ij} v_{ijt\omega}^{P+} \tag{24}$$

$$P_{ijt\omega}^{-} \le V_{\text{nom}} \overline{I}_{ij} v_{ijt\omega}^{P-} \tag{25}$$

$$Q_{ijt\omega}^{+} \le V_{\text{nom}} \overline{I}_{ij} v_{ijt\omega}^{Q+} \tag{26}$$

$$Q_{ijt\omega}^{-} \le V_{\text{nom}} \overline{I}_{ij} v_{ijt\omega}^{Q-} \tag{27}$$

$$v_{ijt\omega}^{P+} + v_{ijt\omega}^{P-} \le y_{ij} \tag{28}$$

$$v_{ijt\omega}^{Q+} + v_{ijt\omega}^{Q-} \le y_{ij}. \tag{29}$$

C. Radial Configuration

The configuration of the network is radial by introducing constraint (30), i.e., the number of closed switches in any loop has to be less than the total number of switches in that loop. Therefore, by having at least one open branch in a loop, only a radial configuration of the network is feasible with the possibility of having one or more radial island(s) [29], [30]

$$\sum\nolimits_{ij} C_{ij} y_{ij} \le N_{\text{loop}} - 1. \tag{30}$$

Obviously, a branch between nodes i and j is disconnected in case of a contingency in that branch. Therefore, binary parameter C_{ij} is added to (30) to show that the branch is open in the mentioned case.

D. Linearization Procedure

The applied equations in the optimization problem are linear, excluding (22), which makes the model nonlinear. To cope with this problem, a linear approximation is proposed [31]. Both the left and right sides of (22) are nonlinear and both should be linearized separately. Note that $V_{jt\omega}^2$ and $I_{ijt\omega}^2$ are variables that represent the square magnitude values of voltages and currents, respectively, and they are used in (15)–(19), (22), and (23). In the following, the linearization process of (22) is described.

1) $V_{jt\omega}^2 I_{ijt\omega}^2$: The product of two variables is linearized by discretizing $V_{it\omega}^2$ in small intervals. However, this leads to an increase in the number of binary variables and computation time. Since the voltage magnitude is within small range in EDS, a constant value V_{nom}^2 is selected and substituted for $V_{jt\omega}^2$ in (22) for the first iteration. Then, the model is run again and $V_{jt\omega}^2$ takes the value resulting from the first iteration. Note that $V_{jt\omega}^2$ hardly changes after the second iteration.

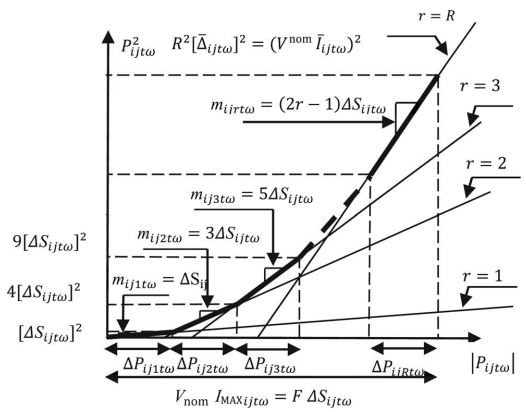

Fig. 2. Modeling the piecewise linear function $P^2_{ijt\omega}$.

2) $P^2_{ijt\omega} + Q^2_{ijt\omega}$: The linearization of both terms on the right side of (22) is carried out by a piecewise linear approximation, as follows:

$$P^2_{ijt\omega} + Q^2_{ijt\omega} = \sum\nolimits_r (m_{ijrt\omega}\Delta P_{ijrt\omega}) + \sum\nolimits_r (m_{ijrt\omega}\Delta Q_{ijrt\omega}) \tag{31}$$

$$P^+_{jit\omega} + P^-_{jit\omega} = \sum\nolimits_r \Delta P_{ijrt\omega} \tag{32}$$

$$Q^+_{jit\omega} + Q^-_{jit\omega} = \sum\nolimits_r \Delta Q_{ijrt\omega} \tag{33}$$

$$0 \le \Delta P_{ijrt\omega} \le \Delta S_{ijrt\omega} \tag{34}$$

$$0 \le \Delta Q_{ijrt\omega} \le \Delta S_{ijrt\omega} \tag{35}$$

where

$$m_{ijrt\omega} = (2r-1)\,\Delta S_{ijrt\omega} \tag{36}$$

$$\Delta S_{ijrt\omega} = \left(V_{\text{nom}}\bar{I}_{ij}\right)/R^{\text{tot}} \tag{37}$$

Note that $m_{ijrt\omega}$ and $\Delta S_{ijrt\omega}$ are constant parameters and (32) and (33) are a set of linear expressions. Likewise, (31) is a linear approximation of $(P^2_{ijt\omega} + Q^2_{ijt\omega})$ and, (32) and (33) represent that $(P^+_{jit\omega} + P^-_{jit\omega})$ and $(Q^+_{jit\omega} + Q^-_{jit\omega})$ are equal to the sum of the values in each section of the discretization. As shown in (31)–(33) and Fig. 2, the right side of (22) can be replaced with the right side of (31) to form a linear equation

$$V^2_{\text{nom}} I^2_{ijt\omega} = \sum\nolimits_r (m_{ijrt\omega}\Delta P_{ijrt\omega}) + \sum\nolimits_r (m_{ijrt\omega}\Delta P_{ijrt\omega}). \tag{38}$$

The linear form of (22) is shown in (38). In this equation, V^2_{nom} is constant and $\sum_r (m_{ijrt\omega}\Delta P_{ijrt\omega})$ and $\sum_r (m_{ijrt\omega}\Delta Q_{ijrt\omega})$ are linear. The linearization of the active power flow is shown in Fig. 2.

IV. Case Studies

A. Network Overview

To evaluate the behavior of the proposed model, a 69-node network is considered and network data come from [32]. Fig. 3 depicts the 69-node network where the green nodes are not connected to loads and the locations of wind turbines and storage units are represented. The network is connected to a substation at node 1. The network contains 74 branches, 5 sectionalizing switches, and 5 tie-switches as shown in Table I, considering negligible opening and closing operation costs.

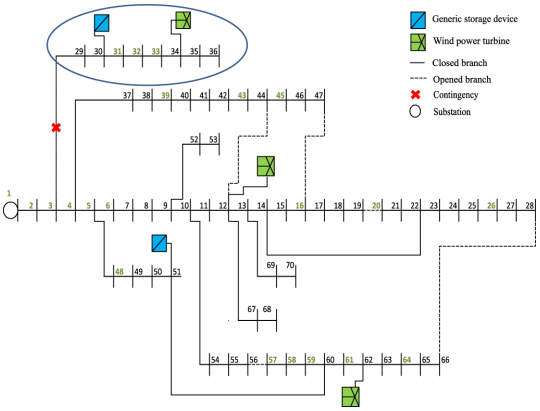

Fig. 3. 69-node network topology under a contingency in branch 3-29.

TABLE I
Switch Data for the 69-Node System

Sectionalizing switches			Tie switches		
12–44	14–22	16–47	7–8	19–20	31–32
28–66	51–60	–	41–42	56–57	–

TABLE II
Cost Data for 69-Node System ($/MWh)

C^{loss}	C^{w_curt}	C^{d_curt}	C^{ss}	C^{sp}	C^{rs}	C^{rp}	$\hat{C}^{\text{rs}}$	$\hat{C}^{\text{rp}}$
5	200	250	0.5	0.1	0.5	0.1	0.5	0.1

Other network costs are shown in Table II. The maximum current flow in the branches is 150 A, excluding branches L_{1-2} (line from nodes 1 to 2), L_{2-3}, and L_{3-4} with a maximum current limit of 100 A. Since the voltage values vary through iterations, the upper and lower voltage limits are defined as 1.1 and 0.9 p.u., respectively. In the linearization, 20 discrete blocks are considered. The total real power demand is 1.103 MW and the total time horizon is 1 h divided into 10 min periods. The demand data, recorded every 10 min, is collected from the Iberian Electricity Market [33], on March 20, 2014, and the contingency is assumed to occur at 4 A.M. Moreover, wind turbines are located at nodes 12, 34, and 62 with a production share of 16%, 34%, and 50%, respectively, and the total installed wind generation capacity is 0.45 MW. Two equal storage units are located at nodes 30 and 51, with a capacity of 0.15 MW allocated to each, and their initial energy levels are set to 50% of their capacities. The upper and lower limits of power storage/production in ESS are 0.075 MW.

B. Wind Production Scenarios

The exploitation of RES, especially wind, has had an upward trend leading to intermittency and uncertainty of power

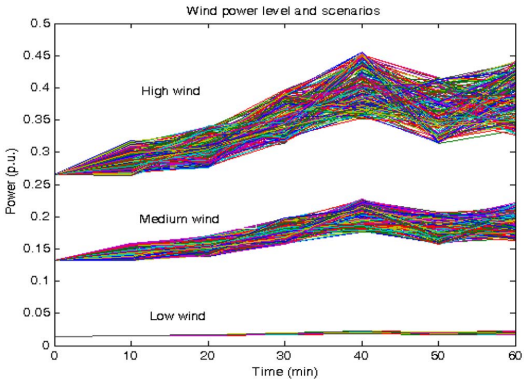

Fig. 4. Three different wind power point forecast and stochastic scenarios.

generation. In order to analyze the network under different conditions, three different stochastic levels of wind generation are introduced (low, mean, and high) as 1.5%, 16%, and 34% of the total demand. In this regard, to represent intermittency of wind power, 200 wind scenarios have been generated randomly by implementing Monte Carlo simulation under a cone of uncertainty, with the maximum error of 15% in 1 h for each forecast, as applied in [34] and [35]. The number of wind scenarios has been limited to 10 to minimize the dimensionality in the problem formulation maintaining accuracy in the results, by implementing a clustering mechanism, the K-means method, taking into account sequences of wind values every 10 min (six values) per scenario. This method can be used to partition a given set of scenarios into a given number of clusters. As a result of this partition, scenarios with similar features are assigned to the same cluster. The centroid of each cluster represents a somewhat average pattern of all the scenarios included in a cluster. Since this centroid is artificial, the original scenario with the lowest probability distance from the centroid is used to represent the cluster [36]. Three levels of wind power generation and their corresponding scenarios are illustrated in Fig. 4. Due to the different PF of loads, commonly between 0.7 and 0.9, reactive power compensation is considered in wind turbines to keep grid security especially in case of islanding.

C. Contingency Analysis

In order to analyze the benefits of introducing renewable generation and storage units in EDS, three case studies under an $N-1$ criterion are represented: 1) CA without RES and ESS; 2) CA including RES; and 3) CA including RES and ESS. This is performed by implementing a contingency parameter C_{ij} per branch to locate the fault in the network. The results are shown in terms of demand and wind curtailment cost (Table III), active power losses (Table IV), and production and storage cost (Table V).

1) Case Study 1—CA Without RES and ESS: In this case, the only power resource is the power injection from the substation to the disturbed system. Consequently, the total power losses are more than the other case studies due to the location of loads at remote nodes. Also, in some situations, a contingency leads to the isolation of the network from the substation, e.g., C_{1-2} (a contingency in the branch between nodes 1 and 2) or C_{2-3} resulting in a blackout. Regarding power losses, some selected results are shown in Table IV. For case study 1, the highest amount is related to C_{60-61} and C_{61-62}. In this case, due to the significant amount of load at node 62, which is far from the power source, power losses increase dramatically.

TABLE III
$N-1$ CONTINGENCY CURTAILMENT COST ANALYSIS ($)

Demand curtailment cost ($)							
Cont.	Case 1	Case 2			Case 3		
		Low	Mean	High	Low	Mean	High
C_{1-2}	275.75	271.15	231.75	188.47	233.66	194.5	151.34
C_{2-3}	275.75	271.15	231.75	188.47	233.66	194.5	151.34
C_{3-4}	268	266.84	248.25	226.48	248.19	227.5	205.63
C_{3-29}	29	5.30	0	0	0	0	0
C_{4-5}	5.04	0	0	0	0	0	0
C_{5-48}	2.38	0	0	0	0	0	0
C_{9-52}	3.66	3.66	3.66	3.66	3.66	3.66	3.66
C_{12-67}	2.99	2.99	2.99	2.99	2.99	2.99	2.99
C_{13-69}	4.64	4.64	4.64	4.64	4.64	4.64	4.64
C_{29-30}	5.39	3.14	0	0	0	0	0
C_{30-31}	3.24	0.98	0	0	0	0	0
C_{31-32}	3.24	0.98	0	0	0	0	0
C_{32-33}	3.24	0.98	0	0	0	0	0
C_{33-34}	3.24	0.98	0	0	0	0	0
C_{34-35}	2.10	2.10	2.10	2.10	2.10	2.10	2.10
C_{35-36}	0.48	0.48	0.48	0.48	0.48	0.48	0.48
C_{48-49}	2.38	0	0	0	0	0	0
C_{49-50}	1.64	0	0	0	0	0	0
C_{50-51}	0.58	0	0	0	0	0	0
C_{52-53}	0.30	0.30	0.30	0.30	0.30	0.30	0.30
C_{60-61}	21.7	0	0	0	0	0	0
C_{61-62}	21.7	0.22	0	0	0	0	0
C_{67-68}	1.49	1.49	1.49	1.49	1.49	1.49	1.49
C_{69-70}	2.32	2.32	2.32	2.32	2.32	2.32	2.32

Wind curtailment cost ($)						
Cont.	Case 2			Case 3		
	Low	Mean	High	Low	Mean	High
C_{3-29}	0	10.6	28.18	0	0	11.98
C_{29-30}	0	12.6	30.19	0	0	13.95
C_{30-31}	0	14.8	32.06	0	14.8	32.06
C_{31-32}	0	14.8	32.06	0	14.8	32.06
C_{32-33}	0	14.8	32.06	0	14.8	32.06
C_{33-34}	0	14.8	32.06	0	14.8	32.06

TABLE IV
$N-1$ CONTINGENCY LOSS ANALYSIS

Losses (kW)							
Cont.	Case 1	Case 2			Case 3		
		Low	Mean	High	Low	Mean	High
C_{1-2}	0	0.02	0.33	1.29	0.06	0.61	1.84
C_{2-3}	0	0.02	0.33	1.29	0.06	0.55	1.84
C_{3-4}	0.08	0.01	0.27	1.23	0.03	0.27	1.17
C_{3-29}	39.41	22.79	25.85	27.06	22.31	19.99	24.62
C_{4-5}	98.82	82.7	74.98	59.97	74.04	66.22	50.69
C_{4-37}	40.53	28.39	21.46	19.93	27.73	20.67	18.74
C_{5-6}	40.56	29.38	21.47	18.07	28.47	20.68	17.52
C_{5-48}	85.04	71.64	60.99	50.61	58.97	50.46	41.07
C_{29-30}	39.42	24.56	23.6	19.63	23.72	21.02	24.24
C_{30-31}	38.66	24.41	21.59	18.13	23.53	21.09	17.03
C_{31-32}	38.66	24.41	21.59	18.13	23.53	20.8	17.03
C_{32-33}	38.66	24.41	21.59	18.13	23.53	20.55	17.03
C_{33-34}	38.66	24.41	21.59	18.13	23.53	20.55	17.03
C_{34-35}	38.68	24.47	20.52	20.05	23.71	19.7	16.66
C_{35-36}	38.72	25.31	20.6	17.18	24.31	19.73	16.49
C_{59-60}	38.74	25.31	20.5	17.58	23.57	19.71	17.43
C_{60-61}	314.82	68.19	55.06	43.20	69.43	54.47	40.75
C_{61-62}	314.82	68.19	55.06	43.20	69.43	54.77	40.75
C_{62-63}	35.21	24.43	21.2	18.17	23.69	20.1	17.63

TABLE V
$N-1$ CONTINGENCY STORAGE COST ANALYSIS ($)

Contingency	C^{sp}	C^{rp}	$\hat{C}^{rp}$	C^{ss}	C^{rs}	$\hat{C}^{rs}$
Low level of wind						
C_{1-2}	0.0135	0	0	0	0	0
C_{2-3}	0.0135	0	0	0	0	0
C_{3-29}	0.0085	0.0003	0.0002	0	0	0
C_{29-30}	0.0077	0.0003	0.0002	0	0	0
Other branches	0.0135	0	0	0	0	0
Mean level of wind						
C_{1-2}	0.0125	0.0024	0.0010	0	0	0
C_{2-3}	0.0124	0.0025	0.0011	0	0	0
C_{3-29}	0.0068	0	0	0.021	0.014	0.0085
C_{29-30}	0.0068	0	0	0.0154	0.0071	0.0008
Other branches	0.0135	0	0	0	0	0
High level of wind						
C_{1-2}	0.0135	0	0	0	0	0
C_{2-3}	0.0135	0	0	0	0	0
C_{3-29}	0.0068	0	0	0.021	0.014	0.014
C_{29-30}	0.0068	0	0	0.0154	0.0071	0.0071
Other branches	0.0135	0	0	0	0	0

In addition, demand curtailment (see Table III), especially for C_{60-61} and C_{61-62}, is remarkable due to the high amount of demand at node 62 and the power flow limitation of the connection branches.

2) Case Study 2—CA Including RES: An obvious difference with respect to case study 1 is the reduction of power losses. As shown in Table IV, real power losses drop roughly 50% for most contingencies considering the mean level of wind generation. The reduction of power losses is expected due to the availability of wind power for local loads. Although the maximum power losses are relevant to contingency C_{4-5}, power losses for C_{60-61} and C_{61-62} are still remarkable. In case of contingency C_{4-5}, the main connection branch to transfer power from the substation to the remote loads is disconnected and power losses are unavoidable, however, as shown in Table III, demand curtailment is zero, in this case. Moreover, total demand curtailment is reduced in some cases, especially for contingencies C_{60-61} and C_{61-62}, due to the availability of wind power for loads at node 62.

In case of low wind generation, the amount of demand curtailment cost and power losses are similar to Case 1, as wind power generation feeds very few loads.

In addition, C_{1-2}, C_{2-3}, and C_{3-4} create an island for the whole network and, despite demand curtailment reduction under these conditions (unlike case study 1), the main part of the demand is not served yet, due to a lack of real power generation. Likewise, an island appears in case of contingency C_{3-29} for a part of the network, as shown in Fig. 3. Here, the mean level of wind generation is able to meet the demand in this area, however, wind curtailment is inevitable due to the imbalance of load and generation. Lastly, since nodes 31, 32, and 33 are not connected to any load, wind curtailment is equal for contingencies C_{30-31}, C_{31-32}, C_{32-33}, and C_{33-34}, as shown in Table III. Since the demand is constant in islanding situations ($C_{1-2}, C_{2-3}, C_{3-4}, C_{3-29}$, and C_{29-30}) by increasing the level of wind production (from a low level to higher levels), the cost of wind curtailment rises. On the other hand, with more wind power production, more loads can be fed, thus, the cost of demand curtailment drops.

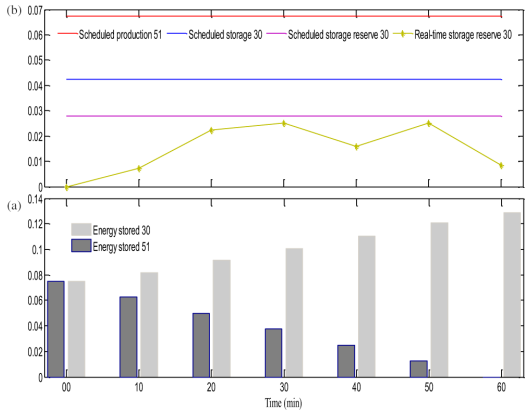

Fig. 5. Energy production/storage under a contingency in branch 3-29. (a) Energy stored (p.u.). (b) Power produced/stored (p.u.).

3) Case Study 3—CA Including RES and ESS: Using mean wind production level and compared with case study 2, ESS reduces power losses, wind and demand curtailment slightly. As illustrated in Table IV, excluding C_{1-2}, C_{2-3}, and C_{3-4}, in the other cases, power losses are reduced moderately. In spite of a fair growth of power losses for C_{1-2}, C_{2-3}, and C_{3-4} (see Table IV), the reduction of demand curtailment is noticeable, as shown in Table III. Storage units improve the operation of the network, particularly in case of islanding for the whole or a part of the network.

As shown in Table III, in cases with islanding, i.e., C_{1-2}, C_{2-3}, and C_{3-4}, the total load connected to the network is increased compare with case study 2. Likewise, for C_{3-29}, the total wind generation capacity is exploited in the presence of a storage unit in the isolated area.

In extreme situations with a high level of wind in islanding areas, as in C_{3-29} and C_{29-30}, the storage units store the extra power production to avoid demand curtailment and minimize their costs.

Since demand is higher than generation in some isolated (C_{1-2}, C_{2-3}, and C_{3-4}) areas, with a higher level of wind generation, wind and demand curtailments decrease.

As presented in Table IV, with a higher level of wind production, excluding islanding conditions, the power losses decline due to the availability of local power for loads.

Fig. 5 shows the behavior of the storage units with mean wind production in case of contingency C_{3-29}. In Fig. 5(a), the energy level of the storage units is illustrated. As C_{3-29} creates an isolated area with more generation than load, the storage unit in that section (node 30) is scheduled to store energy to avoid wind curtailment. On the other hand, the storage unit at node 51 is scheduled to produce and compensate the lack of real power.

Fig. 5(b) shows the real-time power storage of unit 30 (green line). Real-time production/storage is represented when the

TABLE VI
RECONFIGURATION ANALYSIS: OPEN SWITCHES

Cont.	Open switches	Cont.	Open switches
C_{1-2}	7-8 12-44 14-22 16-47 28-66 56-57	C_{28-66}	12-44 16-47 19-20 56-57
C_{2-3}	7-8 12-44 14-22 16-47 28-66 56-57	C_{29-30}	12-44 16-47 19-20 28-66 56-57
C_{3-4}	7-8 12-44 14-22 16-47 28-66 56-57	C_{30-31}	12-44 16-47 19-20 28-66 56-57
C_{3-29}	12-44 16-47 19-20 28-66 56-57	C_{31-32}	12-44 16-47 19-20 28-66 56-57
C_{4-5}	16-47 19-20 28-66 56-57	C_{32-33}	12-44 16-47 19-20 28-66 56-57
C_{4-37}	16-47 19-20 28-66 56-57	C_{33-34}	12-44 16-47 19-20 28-66 56-57
C_{5-6}	12-44 14-22 19-20 56-57	C_{34-35}	12-44 16-47 19-20 28-66 56-57
C_{5-48}	12-44 14-22 16-47 28-66	C_{35-36}	12-44 16-47 19-20 28-66 56-57
C_{6-7}	12-44 14-22 19-20 56-57	C_{37-38}	16-47 19-20 28-66 56-57
C_{7-8}	12-44 14-22 19-20 56-57	C_{38-39}	16-47 19-20 28-66 56-57
C_{8-9}	12-44 14-22 19-20 56-57	C_{39-40}	16-47 19-20 28-66 56-57
C_{9-10}	12-44 14-22 19-20 56-57	C_{40-41}	16-47 19-20 28-66 56-57
C_{9-52}	16-47 19-20 28-66 41-42 56-57	C_{41-42}	16-47 19-20 28-66 56-57
C_{10-11}	16-47 19-20 28-66 56-57	C_{42-43}	16-47 19-20 28-66 56-57
C_{10-54}	12-44 14-22 16-47 19-20	C_{43-44}	16-47 19-20 28-66 56-57
C_{11-12}	12-44 19-20 28-66 56-57	C_{44-45}	12-44 19-20 28-66 56-57
C_{12-13}	12-44 19-20 28-66 56-57	C_{45-46}	12-44 19-20 28-66 56-57
C_{12-44}	16-47 19-20 28-66 56-57	C_{46-47}	12-44 19-20 28-66 56-57
C_{12-67}	12-44 14-22 19-20 56-57	C_{48-49}	12-44 14-22 16-47 28-66
C_{13-14}	12-44 19-20 28-66 56-57	C_{49-50}	12-44 14-22 16-47 28-66
C_{13-69}	12-44 14-22 19-20 56-57	C_{50-51}	12-44 14-22 16-47 28-66
C_{14-15}	12-44 19-20 28-66 56-57	C_{51-60}	12-44 16-47 19-20 28-66
C_{14-22}	16-47 28-66 41-42 56-57	C_{52-53}	16-47 19-20 28-66 41-42 56-57
C_{15-16}	12-44 19-20 28-66 56-57	C_{54-55}	12-44 14-22 16-47 28-66
C_{16-17}	12-44 16-47 28-66 56-57	C_{55-56}	7-8 16-47 19-20 28-66
C_{16-47}	12-44 19-20 28-66 56-57	C_{56-57}	7-8 16-47 19-20 28-66
C_{17-18}	12-44 16-47 28-66 56-57	C_{57-58}	7-8 12-44 14-22 28-66 56-57
C_{18-19}	12-44 16-47 28-66 56-57	C_{58-59}	7-8 12-44 14-22 28-66 56-57
C_{19-20}	12-44 16-47 28-66 56-57	C_{59-60}	7-8 14-22 26-47 28-66 56-57
C_{20-21}	12-44 16-47 19-20 28-66 56-57	C_{60-61}	7-8 12-44 14-22
C_{21-22}	12-44 16-47 19-20 28-66 56-57	C_{61-62}	7-8 12-44 14-22
C_{22-23}	12-44 16-47 19-20 56-57	C_{62-63}	16-47 19-20 41-42 56-57
C_{23-24}	12-44 16-47 19-20 56-57	C_{63-64}	16-47 19-20 41-42 56-57
C_{24-25}	12-44 16-47 19-20 56-57	C_{64-65}	12-44 16-47 19-20 56-57
C_{25-26}	12-44 16-47 19-20 56-57	C_{65-66}	12-44 16-47 19-20 56-57
C_{26-27}	12-44 16-47 19-20 56-57	C_{67-68}	12-44 14-22 19-20 56-57
C_{27-28}	12-44 16-47 19-20 56-57	C_{69-70}	12-44 14-22 19-20 56-57

scheduled production/storage of energy is not sufficient to compensate the power imbalance with mean wind production of the network, as it occurs for storage unit 30.

Table V contains the costs of the storage units per contingency. The total costs of the storage units are lower than the other costs in the network and, in that regard, they are efficient. With high wind production, in C_{3-29} and C_{29-30}, the storage units in isolated areas store more in real time to avoid wind curtailment. On the other hand, with low wind power, the ESS units produce in real time to compensate the power imbalance.

D. Reconfiguration Analysis

Network reconfiguration is important to analyze to meet some goals such as reduction of power losses and isolation of faults in the EDS. In this paper, reconfiguration is carried out under contingency conditions to reach the optimal point of the optimization problem. As mentioned before, Table I shows the status of the switches in the EDS. Initially, under normal conditions, S_{12-44} (switch between nodes 12 and 44), S_{16-47}, S_{19-20}, S_{28-66}, and S_{56-57} are normally open and others are normally closed. The status of the open switches is represented for case studies 2 and 3 (for the mean value of wind) in Table VI, which is the same for both cases.

In case of contingencies C_{1-2}, C_{2-3}, and C_{3-4}, the same reconfiguration is defined by the optimization problem splitting the EDS into two radial islands, one having wind only, and the other having wind and storage. Therefore, in case of disconnection of the EDS from the external grid, the optimization problem can manage the EDS to be energized avoiding a blackout in the isolated part. Noteworthy, demand and generation curtailment is reduced by having separated radial islands in areas isolated from the substation. In order to feed loads next to the contingency and to avoid demand curtailment, the optimization problem decides to close the switches near loads. On the other hand, contingencies C_{57-58}, C_{58-59}, C_{59-60}, and C_{56-57} occur near to nodes without any connected loads and the switches in these areas remain open under any condition.

TABLE VII
COMPUTATION TIME (S)

Case 1	Case 2	Case 3
793.8	9262	11071

In addition, the location of both, generation and contingency, influences the RDS. For instance, S_{31-32} and S_{51-60} are always closed, as they are near to generation and storage units. Finally, reconfiguration of the EDS is not changed for contingencies in branches close to each other, as in cases L_{5-51} (feeder from nodes 5 to 51), L_{7-10}, L_{12-68}, L_{13-70}, L_{24-28}, L_{29-36}, and L_{37-44}.

All case studies have been solved using CPLEX 11 solver in GAMS [37]. An Intel Xeon E7-4820 computer with four processors at 2 GHz and 128 GB of RAM has been used. MATLAB [38] has been used to implement scenario reduction using K-means. Table VII illustrates the computation time of every case study assuming a mean wind power and for all the contingencies. Note that, the CPU times in Table VII correspond to the whole set of contingencies for each case, which are solved one by one. It could be possible to reduce the CPU time by analyzing the branches, which are more likely to be out of operation. The CPU time could be further reduced by considering a lower number of linearization blocks.

V. CONCLUSION

In this paper, a two-stage stochastic MILP reconfiguration model under $N-1$ contingency conditions, considering wind energy and ESS with the possibility of having isolated radial grids in distribution systems, has been investigated.

An exhaustive analysis has been done to evaluate the model and, as a result, the model has been successfully applied to a distribution network to minimize total costs. Following that, the work shows the advantages of having energy storage units and renewable energy in terms of real-time operation under contingencies in distribution networks. Consequently, the penetration of storage devices and wind generation improves the operation of the network under contingency conditions and reduces power losses and demand and generation curtailment. In addition, this method improves reliability, allows for an optimal radial reconfiguration, radial islanded operation, and the reduction of real power losses. Storage units improve the operation of the network, especially in case of islanding for the whole network or a part of it. The location of storage units is important to compensate local power, i.e., power injection to local

demand and absorption of additional power from local generation. In conclusion, the proposed model can be a valuable tool for an electrical distribution company to optimally reconfigure the system by evaluating all possible contingencies of the network using wind power and energy storage.

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Chapter 3

Islanding in Distribution Systems Considering Wind Power and Storage

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Islanding in distribution systems considering wind power and storage

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ABSTRACT

In modern power systems the penetration of renewable energies has been growing dramatically. The combination of renewable energy and energy storage is seen as an opportunity to better exploit the intermittent and uncertain local generation in distribution systems, especially in the case of islanding. The main goal of this paper is to keep the load and generation units on-line under islanding conditions with respect to the total power imbalance of the isolated area and minimizing the power losses and nodal voltage deviations. A two-stage stochastic linear programming model is introduced to solve the optimization problem and find the best combination of generation, demand and electrical energy storage under islanding conditions. The proposed model has been tested on a 69-bus distribution system and the results obtained in the islanded areas are presented considering two case studies (with and without electrical energy storage), under different levels of generation and demand.

1. Introduction

Currently, regulatory agencies are highly committed to increasing the integration of Renewable Energy Sources (RES) due to their global interest and benefits, including economic and ecological advantages. Likewise, several types of Energy Storage Systems (ESS) are being developed and applied in electrical networks to cope with problems such as smoothing the output power of RES [1], improving power system stability [2,3] and being economically efficient [4]. On the other hand, the penetration of RES, especially wind power, creates several problems regarding their intermittency and uncertainty [5,6]. In particular, to manage and increase the penetration of RES and ESS in electrical networks, an innovative procedure is required for both normal and abnormal conditions. Although having RES and ESS in electrical networks creates challenges to integrate them within Electrical Distribution Systems (EDS), exploiting RES and ESS in abnormal conditions like islanding can be seen as an opportunity to use more generation and demand within the island.

Islanding in power systems may be intentional or unintentional. Due to large frequency perturbations or contingency plans, intentional islanding is planned in advance in power systems to cope with problems in the network. On the other hand, unintentional islanding may occur due to the automatic response of the protection system to a fault happening in radial systems. In this case, it may be more challenging to define the islanded area conditions and guarantee the success of the islanding procedure.

In power systems, especially those with islanding conditions, supply and demand have to be balanced in real-time due to the fact that electrical energy cannot be stored efficiently in large amounts. An imbalance between supply and demand leads to several problems, such as frequency and voltage deviation in the power grid. Therefore, the definition of a predefined procedure able to keep the islanded area energized and avoid complete blackout becomes essential.

Several works have been carried out to deal with the disconnection from the bulk power system creating islands. For example, in [7–9] the configuration and control of islanding in a random way based on the topology of the grid is presented. A two-step algorithm is introduced in [10] using spectral clustering to find suitable islanding. In [11], a time domain simulation is presented to control islanding by dividing a bulk power system into several pre-selected islands. In some works, load shedding is minimized under intentional islanding conditions [12–14]. A review regarding research on planned islanding operation for a rotating type of distributed generation with a particular focus on small hydro generation is presented in [15]. A load shedding and generator tripping logic for proper islanding is developed in [16], based on detailed power system studies. An evolutionary algorithm based on current limiting protectors for controlled islands in distribution systems is presented in [17]. An islanding control approach based

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Nomenclature

Indexes

i, j, k	Bus indexes
r	Piecewise linearization (PWL) block index
t	Real-time period index on a 10-min basis
ω	Scenario index

Parameters

$\hat{C}^{rs}$	Real-time storage cost of the storage unit ($/MWh)
$\hat{C}^{rp}$	Real-time production cost of the storage unit ($/MWh)
C^{sw}	Cost of switching
$d_{it\omega}$	Real power demand (MW)
f^{loss}	Power losses penalization weight factor
f^{V_dev}	Voltage deviation penalization weight factor
C^{W_curt}	Wind curtailment cost
C^{d_curt}	Real power demand curtailment cost
ini_{ij}	Initial state of switches
$\bar{I}_{ij}$	Maximum current flow through branch ij (A)
$m_{ijrt\omega}$	Slope of the rth block of the PWL
N_{loop}	Number of buses in a loop
N_B	Number of branches of the network
N_N	Number of nodes of the network
N_R	Number of blocks of the PWL
N_T	Number of time intervals
N_W	Number of scenarios
$P^{d\_fore}_{it\omega}$	Demand forecast (MW)
$P^{w\_fore}_{it\omega}$	Wind power forecast (MW)
PF^d_i	Power factor of the demand
PF^{wind}_i	Power factor of the wind turbines
$q_{it\omega}$	Reactive power demand (Mvar)
r^p_i, r^s_i	Scheduled power production/storage reserve (MW)
R_{ij}	Resistance of branch ij (Ω)
R^{tot}	Total number of blocks in the PWL
$V'^{\ 2}_{it\omega}$	Approximation of the voltage magnitude of node i (kV)
V_{ref}	Nominal voltage of the distribution network (kV)
$\underline{V}, \overline{V}$	Minimum/maximum voltage of the distribution network (kV)
$\overline{W}^2$	Upper bound of variable $W^2_{ijt\omega}$ (kV^2)
x^s_0	Initial energy level of storage (MWh)
$\underline{x}_i, \overline{x}_i$	Minimum/maximum storage capacity at node i (MWh)
X_{ij}	Reactance of branch ij (Ω)
Z_{ij}	Impedance of branch ij (Ω)
$\Delta S_{ijrt\omega}$	Upper bound of the rth block of the power flow
γ	Reactive power control parameter
η^s_i, η^p_i	Efficiency rate of the storage units
Δ	Real-time period (10 min) (h)

Non-negative variables

$I^2_{ijt\omega}$	Square of the current flow through branch ij (A^2)
$P^{wind}_{it\omega}$	Real power of wind turbine at bus i (MW)
$P^{dem}_{it\omega}$	Real power of demand at bus i (MW)
$P^{w\_curt}_{it\omega}$	Real power wind curtailment at bus i (MW)
$P^{d\_curt}_{it\omega}$	Real power demand curtailment at bus i (MW)
$P^+_{ijt\omega}$	Real power flow (downstream) (MW)
$P^-_{ijt\omega}$	Real power flow (upstream) (MW)
$Q^+_{ijt\omega}$	Reactive power flow (downstream) (Mvar)
$Q^-_{ijt\omega}$	Reactive power flow (upstream) (Mvar)
$\hat{r}^p_{it\omega}, \hat{r}^s_{it\omega}$	Real-time production/storage reserve (MW)
$V^2_{it\omega}$	Square of the voltage magnitude of node i (kV^2)
$W^2_{ijt\omega}$	Variable related to the voltage drop (kV^2)
$\hat{x}_{it\omega}$	Storage level at node i (MWh)
$\Delta P_{ijrt\omega}$	Value of the rth block of real power (MW)
$\Delta Q_{ijrt\omega}$	Value of the rth block of reactive power (Mvar)

Free variables

$Q^{wind}_{it\omega}$	Reactive power of wind generation (Mvar)
$Q^{dem}_{it\omega}$	Reactive power of demand (Mvar)
$Q^{d\_curt}_{it\omega}$	Reactive power demand curtailment (Mvar)
$Q^{wind+}_{it\omega}$	Reactive power upper bound of wind generation (Mvar)
$Q^{wind-}_{it\omega}$	Reactive power lower bound of wind generation (Mvar)

Binary variables

$v^{p+}_{ijt\omega}$	Variable related to real power (upstream)
$v^{p-}_{ijt\omega}$	Variable related to real power (downstream)
$v^{q+}_{ijt\omega}$	Variable related to reactive power (upstream)
$v^{q-}_{ijt\omega}$	Variable related to reactive power (downstream)
$v^s_{it\omega}, v^p_{it\omega}$	Variables related to power storage or production
y_{ij}	State of the switches in branch ij: 1 if closed, 0 otherwise
$\mu_{ijrt\omega}$	State of the PWL block of real power: 0 if filled, 1 otherwise
$\eta_{ijrt\omega}$	State of the PWL block of reactive power: 0 if filled, 1 otherwise

Functions

ϕ	Total switching cost function
$\psi(\omega)$	Total cost of power losses and voltage deviation
$\kappa(\omega)$	Total costs of wind and demand curtailments and ESS operation

on the optimization of a linear DC power flow is presented in [18] and developed in [19] by implementing a piecewise linear approximation of an AC power flow. The main technical issues to develop control techniques for establishing a microgrid, in case of islanding, are addressed in [20]. In distribution systems, an island partition model with distributed generation and a two-stage branch and bound algorithm is designed in [21]. An innovative islanding feasibility function in subtransmission systems based on reactive power and real power is proposed in [22,23], respectively.

In the technical literature, an optimization procedure considering the combination of wind power with energy storage under islanding conditions in distribution systems has not been presented yet. It is worth mentioning that, due to the intermittency and uncertainty of wind power, the combination of RES and ESS is desirable in case of islanding to improve the reliability and reduce the real power imbalance between load and generation. Consequently, the motivation of this paper is to show the benefits of combining RES with ESS to minimize operational storage system costs, wind and generation curtailment, power losses and voltage deviation of buses. In other words, in this paper, a novel algorithm is presented to keep the load and generation units on-line under islanding conditions with respect to the total power imbalance of the isolated area and minimizing the power losses and nodal voltage deviations.

The study refers to the possibility of supplying the loads, without loss of generality, for a given duration, under islanding conditions after disconnection from the external grid. The basic idea proposed is that islands have to be reconnected to the main network within a given time period. In addition, due to technical reasons such as simplicity of analysis, reduction of the short circuit currents and coordination of the protections, the distribution system and the islands operate with a radial topology.

The approach of this paper is not conceived to encompass real-time control. The model is designed to balance both real and reactive power between load and generation and keep the isolated area energized. In this way, predefined control actions are defined in advance for an initial point. In order to have the right frequency in the desirable area, a balance of active power is introduced and, for voltage deviation, a reactive power balance of load and generation is considered. Consequently, the model is capable to manage the network in abnormal conditions like islanding and separation from the external grid. Of course, every ten minutes the designed model updates the setpoints for the control actions in order to consider the changes in the network after a given time step.

The mathematical formulation of this paper consists of a two-stage stochastic Mixed Integer Linear Programming (MILP) reconfiguration model considering wind energy and energy storage in EDS. Hence, an Alternative Current (AC) power flow is approximated through linear expressions to linearize the model.

Several works have been carried out to linearize the AC power flow in power system studies. In [24] an active network management strategy relying upon short-term policies to control the power of generators and load avoiding congestion or voltage problems is represented. Ref. [25] is divided in two parts. In the first part, the authors discuss about branch convexification and the misinterpretation of the physical model and unrealistic assumption therein. In the second part, two algorithms are proposed to overcome the limitations identified in the first part. A linear programming model incorporating reactive power and voltage magnitude is introduced in [26], where a piecewise linear approximation of the cosine term in the power flow equations is proposed. Two linearization techniques are implemented in [27] in the mixed non-linear programming framework to obtain an equivalent mixed integer linear programming model. In [28,29] a piecewise linear approximation function is applied to approximate the product square value of voltage and current. In [30] the demands of the electric distribution system are modeled with linear approximations in terms of real and imaginary parts of the voltage considering operating conditions of the electric distribution system. In this paper, the approaches of [28–30] are applied to obtain a linear AC power flow formulation to be introduced in the optimization problem.

Noteworthy, the linear model implemented in this paper has the following benefits: (1) is based on a robust mathematical model, (2) the computational behavior of a linear solver is more efficient than non-linear solvers and (3) using classical optimization techniques, convergence can be guaranteed.

The paper is organized as follows. In Section 2, a stochastic model of wind and a generic model of storage system is introduced. Section 3 describes the optimization problem formulated as a stochastic MILP. The case studies are illustrated and explained in Section 4. Results and discussion are presented in Section 5. Finally, Section 6 contains the conclusions.

2. Wind generation and storage units modeling

2.1. Wind production uncertainty modeling

With the expected growth of wind power penetration in electrical networks, it is necessary to consider the intermittency and uncertainty of these resources. Therefore, in order to model wind uncertainty, a probabilistic method based on time series has been implemented, according with the principles indicated in [31].

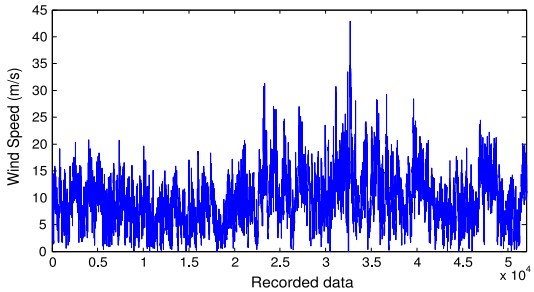


Fig. 1. Historical wind speed data for one year.

Historical data of one year of wind generation [32] are considered as initial data (Fig. 1) and represented through their Cumulative Distribution Function (CDF). Starting from the initial data, in this paper the empirical distribution functions are used instead of constructing Beta distribution functions as in [31]. In this way, the full statistical characteristics of the initial data are preserved. This is the only difference with respect to the procedure applied in [31] for creating a number of wind speed patterns.

The application of the procedure contains the following steps:

(a) Preparatory phase: from the CDF of the historical wind speed, the wind speeds are partitioned into deciles, obtaining the corresponding wind speed ranges with the following upper values: 3.875, 5.425, 6.717, 7.879, 9.171, 10.463, 11.755, 13.434, 16.017 and 42.885 m/s. Then, taking all the wind speeds located in the same decile, the CDF representing the wind speed at the next time step is constructed (all the wind speeds of the next time step reached by starting from a wind speed in the same decile are used to form the CDF).
(b) Choice of the number of scenarios and selection of the initial wind speed: N_W wind speed patterns are constructed, each one starting from a wind speed value randomly selected from the probability distribution of the historical data. The selection mechanism is the classical one, consisting of extracting for each scenario a random number from a uniform probability distribution in (0, 1), entering the CDF of the historical wind speed with that random number and identifying the corresponding wind speed.
(c) Construction of the wind speed time series for each scenario: the decile of the initial wind speed is identified. The CDF of the wind speed at the next time step for that decile is considered, extracting the wind speed from that CDF with the classical selection mechanism indicated above. The decile of the wind speed extracted is identified, the corresponding CDF of the next time step is considered, the new wind speed is extracted, and so forth until all the wind speed values in the time interval of analysis have been extracted.

By using this procedure, the evolution of the individual generated patterns is representative of the evolution of the pattern in the historical data set. In order to show the effectiveness of this procedure, Fig. 2 visualizes the reordered historical data with one-year data at 10-min time steps (thick line), together with the reordered data of 12 patterns constructed for the same one-year duration and 10-min time steps. It is apparent that the sequence of reordered data is quite close to the one of the reordered historical data.

In this paper, the islanding period considered is relatively short (e.g., one hour), and the quantity of interest is the wind

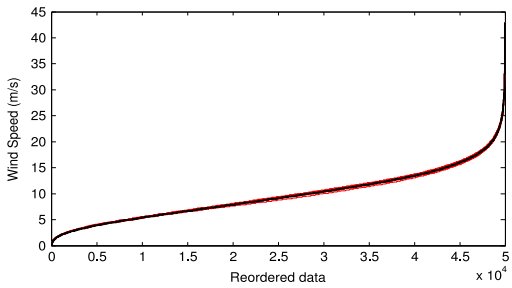


Fig. 2. Reordered wind speed for one year.

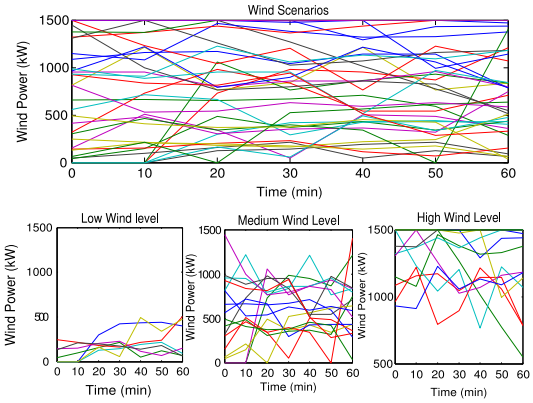


Fig. 3. Different levels of wind and demand in islanded areas.

power obtained from the wind speed by using the manufacturer's curve [33]. For the purpose of the analysis, the N_W wind speed patterns correspond to N_W wind power scenarios, and these scenarios are further grouped into three wind levels (namely, low, medium and high), defined on the basis of the CDF of the average wind speed resulting from the wind speed patterns (Fig. 3). In particular, the lowest 1/3 of wind speeds are associated with the low wind level, the highest 1/3 of wind speeds are associated with the high wind level, and the remaining ones are associated with the medium wind level.

2.2. Generic storage unit model

Several forms of ESS have been identified in EDS, meeting different goals including improving power system reliability, feeding real-time power demand and being economically efficient. In this paper, a generic storage unit model is introduced and applied [34]. The mathematical formulation of the ESS is represented through (1)–(6).

$$0 \le \hat{r}^p_{it\omega} \le r^p_i v^p_{it\omega} \tag{1}$$

$$0 \le \hat{r}^s_{it\omega} \le r^s_i v^s_{it\omega} \tag{2}$$

$$\underline{x}_i \le \hat{x}_{it\omega} \le \overline{x}_i \tag{3}$$

$$\hat{x}_{it\omega} = \hat{x}_{i(t-1)\omega} + \Delta[\eta^s_i \hat{r}^s_{it\omega} - (1/\eta^p_i)\hat{r}^p_{it\omega}] \tag{4}$$

$$\hat{x}_{it\omega=0} = x^s_0 \tag{5}$$

$$v^p_{it\omega} + v^s_{it\omega} \le 1. \tag{6}$$

In the above equations, the actual reserve bounds are defined in (1) and (2). The capacity limits of the ESS is introduced by (3). Eq. (4) shows the storage transition function. Thus, the state of charge, $\hat{x}_{it\omega}$ (storage level at node i, period t and scenario ω), of the ESS located at bus i at the end of time interval t for each scenario ω depends on the previous state of charge, $\hat{x}_{i(t-1)\omega}$, and the power storage/production during the current interval. The initial energy status of the ESS is defined in (5). Finally, in (6), binary variables $v^p_{it\omega}$ and $v^s_{it\omega}$ are defined and added to (1) and (2) to avoid producing and storing energy simultaneously.

3. Stochastic formulation of the problem

The following assumptions are defined to represent the simplified operation of EDS including switches, generation and storage devices:

- The EDS is a balanced three-phase system and can be represented by its equivalent single-phase circuit.
- Shunt line parameters are not considered.
- The islanding duration is predefined. The islanding period is partitioned into time intervals denoted with t. The duration of the time intervals depends on data availability.
- The coupling time of ESS is 10 min (6 time intervals during 1 h).
- Changes in the load patterns in the EDS may occur for each time interval. Inside each time interval all the variables are assumed to be constant.
- The location of storage units has already been defined in the planning phase.
- Losses in the ESS are ignored.

3.1. Objective function

The objective function is formulated by using two-stage stochastic programming as shown in (7)–(10). At the first stage, the costs of switching under islanding conditions regardless of the scenarios ϕ are defined in (8). There, the first term is related to the cost of closing a switch in branch i, j and the second refers to the cost of opening a switch in branch i, j. Noteworthy, at this stage, the status of the switches are defined and will not change during islanding periods. At the second stage, regarding the scenarios, the expected values of the total cost of the real power losses and the voltage deviation with respect to the reference value, $\psi(\omega)$, in branch i, j are penalized in (9). Likewise, the cost of generation and demand curtailment and the real-time production/storage cost in the ESS located at bus i, $\kappa(\omega)$ are considered in (10), for each time interval t, with respect to the different scenarios (ω) and islanding conditions.

At the first stage, the variables are only related to the behavior of the switches, which remains invariant during the whole hour, and at the second stage, other variables are related to scenarios.

$$\min\{\phi + E[\psi(\omega)] + E[\kappa(\omega)]\} \tag{7}$$

$$\phi = \sum_{ij}(y_{ij}C^{sw})\Big|_{ini_{ij}=0} + \sum_{ij}((1-y_{ij})C^{sw})\Big|_{ini_{ij}=1}. \tag{8}$$

In (8), the first and second terms refer to open and closed switches before islanding, respectively.

$$\psi(\omega) = \Delta\left[\sum_t\sum_{ij} R_{ij}I^2_{ijt\omega}f^{loss} + \sum_t\sum_{ij}\left|V^2_{it\omega} - V^2_{ref}\right|f^{V_{dev}}/R_{ij}\right] \tag{9}$$

$$\kappa(\omega) = \Delta\left[\sum_t\sum_i (P^{w\_curt}_{it\omega}C^{w\_curt}_{it\omega} + P^{d\_curt}_{it\omega}C^{d\_curt}_{it\omega} + \hat{r}^p_{it\omega}\hat{C}^{rp} + \hat{r}^s_{it\omega}\hat{C}^{rs})\right]. \tag{10}$$

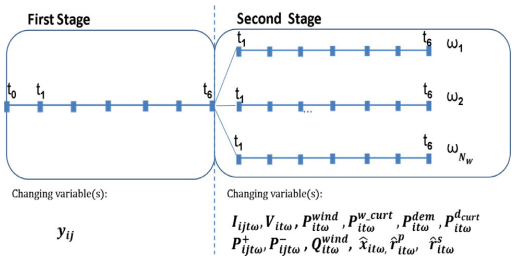


Fig. 4. Two-stage objective function.

The voltage deviation is formally expressed as (11). However, in order to use $V^2_{it\omega}$ as a variable in the MILP model, an approximation is introduced by considering $V_{it\omega} = V_{ref}$ in the last term of (11), as seen in (12).

$$(V_{it\omega} - V_{ref})^2 = \left|V^2_{it\omega} + V^2_{ref} - 2V_{it\omega}V_{ref}\right| \tag{11}$$

$$\left|V^2_{it\omega} + V^2_{ref} - 2V_{it\omega}V_{ref}\right| = \left|V^2_{it\omega} - V^2_{ref}\right|. \tag{12}$$

Fig. 4 illustrates the two-stage objective function. In the first stage, the status of the switches is defined regardless of scenarios and time; in the second stage, several variables are characterized as indicated in the figure.

3.2. Constraints

Various constraints are included in the following mathematical statements to assure optimal operation conditions.

3.2.1. Real-time power balance equations

Eq. (13) is formulated to be implemented in the power balance equation (15).

$$P^{dem}_{it\omega} = P^{d\_fore}_{it\omega} - P^{d\_curt}_{it\omega}. \tag{13}$$

As assumed, wind turbines are able to compensate the reactive power in order to maintain the grid security under islanding conditions. The wind power balance is formulated in (14) and implemented in (15).

$$P^{wind}_{it\omega} = P^{w\_fore}_{it\omega} - P^{w\_curt}_{it\omega}. \tag{14}$$

Real and reactive power balances at node i are formulated in (15) and (16), respectively.

In order to determine the direction of the current and power flow (forward or backward), especially in (15) and (16), two types of positive separate variables applied to both active power ($P^+_{ijt\omega}$, $P^-_{ijt\omega}$) and reactive power ($Q^+_{ijt\omega}$, $Q^-_{ijt\omega}$) are introduced in Fig. 5. Wind power generation, storage/production of ESS and, demand power curtailment and power losses are considered in these constraints.

$$P^{wind}_{it\omega} + \sum_k (P^+_{kit\omega} - P^-_{kit\omega}) - \sum_j [(P^+_{ijt\omega} - P^-_{ijt\omega}) + R_{ij}I^2_{ijt\omega}] + (\hat{r}^p_{it\omega} - \hat{r}^s_{it\omega}) = P^{dem}_{it\omega} \tag{15}$$

$$Q^{wind}_{it\omega} + \sum_k (Q^+_{kit\omega} - Q^-_{kit\omega}) - \sum_j [(Q^+_{ijt\omega} - Q^-_{ijt\omega}) + X_{ij}I^2_{ijt\omega}] = Q^{dem}_{it\omega}. \tag{16}$$

3.2.2. Voltage drop equations

Voltage drops between nodes are formulated in (17), where $W^2_{ijt\omega}$ is an auxiliary variable related to switching operations. In case of open switching at branch i, j, $W^2_{ijt\omega}$ takes into account that there is a voltage drop between bus i and bus j.

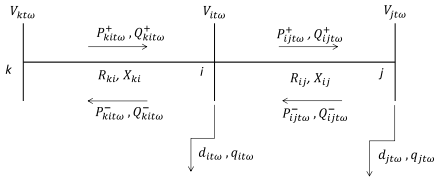


Fig. 5. Illustrative radial distribution system.

$$V^2_{it\omega} - Z^2_{ij}I^2_{ijt\omega} - V^2_{jt\omega} + W^2_{ijt\omega} - 2[R_{ij}(P^+_{ijt\omega} - P^-_{ijt\omega}) + X_{ij}(Q^+_{ijt\omega} - Q^-_{ijt\omega})] = 0. \tag{17}$$

The maximum and minimum voltage variations for bus i are defined in (18). Constraints (19) and (20), state that auxiliary variable $W_{ijt\omega}$ is 0 when branch i, j is in operation ($y_{ij} = 1$). Moreover, $\overline{W}^2$ must be calculated to give enough freedom for variable $W^2_{ijt\omega}$ in order to satisfy constraint (17). The upper bound of this variable is the difference of the square values of the maximum and minimum voltages of the network.

$$\underline{V}^2 \le V^2_{it\omega} \le \overline{V}^2 \tag{18}$$

$$W^2_{ijt\omega} \ge -\overline{W}^2(1 - y_{ij}) \tag{19}$$

$$W^2_{ijt\omega} \le \overline{W}^2(1 - y_{ij}). \tag{20}$$

3.2.3. Current and power magnitude limits

A set of constraints is represented regarding the thermal limits of the EDS. Constraints (21), (22)–(23) and (24)–(25) are introduced for the current, real and reactive power bounds, respectively. Finally, (26) and (27) are set to avoid considering forward and backward power flows simultaneously. Note that (22)–(25) are auxiliary constraints to improve the convergence of the proposed model.

$$0 \le I^2_{ijt\omega} \le \bar{I}^2_{ij}y_{ij} \tag{21}$$

$$P^+_{jit\omega} \le V_{nom}\bar{I}_{ij}v^{P^+}_{ijt\omega} \tag{22}$$

$$P^-_{jit\omega} \le V_{nom}\bar{I}_{ij}v^{P^-}_{ijt\omega} \tag{23}$$

$$Q^+_{jit\omega} \le V_{nom}\bar{I}_{ij}v^{Q^+}_{ijt\omega} \tag{24}$$

$$Q^-_{jit\omega} \le V_{nom}\bar{I}_{ij}v^{Q^-}_{ijt\omega} \tag{25}$$

$$v^{P^+}_{ijt\omega} + v^{P^-}_{ijt\omega} \le y_{ij} \tag{26}$$

$$v^{Q^+}_{ijt\omega} + v^{Q^-}_{ijt\omega} \le y_{ij}. \tag{27}$$

3.2.4. Non-linear apparent power equations

The current flow magnitude is formulated in (28), which is the only non-linear equation in the optimization problem. The linearization procedure is explained in detail in Section 3.3.

$$V^2_{it\omega}I^2_{ijt\omega} = P^2_{ijt\omega} + Q^2_{ijt\omega}. \tag{28}$$

3.2.5. Radiality constraints

Constraint (29) is designed to configure the network in a radial form, which means the number of closed branches in any loop has

to be less than the total number of branches in that loop, as in [35]. The detailed description of the algorithm is presented in [36]. Initially, a Depth-First Search strategy is used to detect all the loops in the network, assuming that the switches are closed. This strategy discovers paths in the network as a sequence of nodes. Therefore, a loop is defined as a closed path with no repeated node excluding the first and last points. In order to maintain the radiality of the system, there should be at least one open branch in each potential loop.

$$\sum_{ij} y_{ij} \leq N_{loop} - 1. \tag{29}$$

3.2.6. Wind reactive power equations

In order to coordinate real and reactive power, the limitations of reactive power for wind turbines are calculated in (29), where $\gamma \geq 1$ is a user-defined coefficient.

$$Q_{it\omega}^{wind^-} = P_{it\omega}^{wind}(\tan(\arccos(-PF_i^{wind}))) \tag{30}$$

$$Q_{it\omega}^{wind^+} = P_{it\omega}^{wind}(\tan(\arccos(PF_i^{wind}))) \tag{31}$$

$$Q_{it\omega}^{wind^-} \leq Q_{it\omega}^{wind} \leq Q_{it\omega}^{wind^+} \tag{32}$$

$$Q_{it\omega}^{wind^+} - Q_{it\omega}^{wind^-} \geq \gamma Q_{it\omega}^{dem}. \tag{33}$$

To apply constraint (33), as mentioned in [22], the islanded area should be divided into reactive control parts, based on the electrical distance measured in the network. However, as the reactive power demand can be compensated by generators and the voltage deviation of the nodes with respect to the reference value is already considered in the model, the separation of the network into islanded areas, based on the mentioned method, is skipped here. In this way, the network is divided into 3 predefined islanded areas regarding the location of the generators and their ability to compensate reactive power for local loads.

3.3. PWL procedure

The mathematical model implemented in this paper is nonlinear due to the constraint appearing in (28). In order to create a linear model, the PWL methods proposed in [28–30] are used here. To create a linear equation from constraint (28), the two sides of the equation should be handled separately. Note that $V_{it\omega}^2$ and $I_{ijt\omega}^2$ are variables that represent the square magnitude values of voltages and currents respectively and they are implemented in (15)–(18) and (21). The linearization process of Eq. (28) is described as follows.

- $V_{jt\omega}^2 I_{ijt\omega}^2$: The left side of (28) is handled by splitting $V_{jt\omega}^2$ into small segments. However, this leads to an increase in the number of binary variables and computation time. In EDS voltage magnitudes are within a small range, so a constant value V_{ref}^2 can be considered as voltage magnitude for the first run of the model in which binary variables are relaxed [28], as shown in (34).

$$V_{jt\omega}^2 I_{ijt\omega}^2 \approx V_{ref}^2 I_{ijt\omega}^2. \tag{34}$$

  Then, the model is run again and $V_{jt\omega}^2$ takes the value resulting from the first run. Note that $V_{jt\omega}^2$ hardly changes after the second execution. Due to the limited range of voltage magnitude variation, this simplification is approximated with a small error.
- $P_{ijt\omega}^2 + Q_{ijt\omega}^2$: Both terms on the right side of (28) are handled by introducing a piecewise linear approximation [29,30]. The process of linearization is presented as follows:

$$P_{ijt\omega}^2 + Q_{ijt\omega}^2 = \sum_r (m_{ijrt\omega}\Delta P_{ijrt\omega}) + \sum_r (m_{ijrt\omega}\Delta Q_{ijt\omega}) \tag{35}$$

$$P_{ijt\omega}^+ + P_{ijt\omega}^- = \sum_r \Delta P_{ijrt\omega} \tag{36}$$

$$Q_{ijt\omega}^+ + Q_{ijt\omega}^- = \sum_r \Delta Q_{ijrt\omega} \tag{37}$$

$$0 \leq \Delta P_{ijrt\omega} \leq \Delta S_{ijrt\omega} \tag{38}$$

$$0 \leq \Delta Q_{ijrt\omega} \leq \Delta S_{ijrt\omega} \tag{39}$$

where:

$$m_{ijrt\omega} = (2r - 1)\Delta S_{ijrt\omega} \tag{40}$$

$$\Delta S_{ijrt\omega} = (V_{nom}\bar{I}_{ij})/R_{ij}. \tag{41}$$

Eq. (35) is a piecewise linear approximation of $(P_{ijt\omega}^2 + Q_{ijt\omega}^2)$, and (36) and (37) represent that $(P_{ijt\omega}^+ + P_{ijt\omega}^-)$ and $(Q_{ijt\omega}^+ + Q_{ijt\omega}^-)$ are equal to the sum of the values in each block of the discretization, which means they are a set of linear terms. In addition, $m_{ijrt\omega}$ and $\Delta S_{ijrt\omega}$ are constant parameters and, (36) and (37) are a set of linear expressions. Therefore, (42) represents the final linear form of constraint (28). In this equation, $V_{jt\omega}^2$ is a parameter and $\sum_r (m_{ijrt\omega}\Delta P_{ijrt\omega})$ and $\sum_r (m_{ijrt\omega}\Delta Q_{ijrt\omega})$ are linear. Fig. 6 shows the PWL of $P_{ijt\omega}^2$.

The model is linear since a PWL has been performed, so, the solution is a global optimum. By increasing the number of blocks, the solution is more accurate, however, the computation time also increases. As performed in several experimental simulations, the solutions hardly change from 20 blocks onwards in the piecewise linear procedure.

$$V_{ref}^2 I_{ijt\omega}^2 = \sum_r (m_{ijrt\omega}\Delta P_{ijrt\omega}) + \sum_r (m_{ijrt\omega}\Delta Q_{ijrt\omega}). \tag{42}$$

In Refs. [28–30] the authors show a set of performance assessments of the approximate method compared with an accurate linearized power flow model (AC). The authors conclude that the error obtained using the piecewise linear approximation may reach a maximum percentage error of 1%.

There are two ways to carry out the PWL of $P_{ijt\omega}^2$ (and also $Q_{ijt\omega}^2$), the one that uses binary variables and another one that does not use them. The use of binary variables to identify in which straight-line of the linearization $P_{ijt\omega}$ is located (when calculating $P_{ijt\omega}^2$) is the most efficient, robust and accurate method, but it is necessary to include many additional binary variables in the model that produce an increase in the computational effort. If no binary variables are used in the linearization, relaxing the adjacency condition is needed to ensure the correct performance of the PWL (see Appendix).

4. Case studies

To assess the behavior of the network in several situations, the proposed model is applied on a 69-bus network. The data of the network is collected from [37]. The maximum current flow in all the lines and the upper bound $\overline{W}^2$ of the auxiliary variable related to the voltage drop are, 90 A and 0.4 kV^2, respectively. Due to the location of loads and generators, the probability of islanding in three areas of the network is anticipated. Therefore, the network is divided into three predefined islanded areas. In particular, the three predefined islanded areas and the location of wind turbines and storage units are represented in Fig. 7. Network specifications are shown in Table 1. In the PWL, 20 discrete blocks are considered.

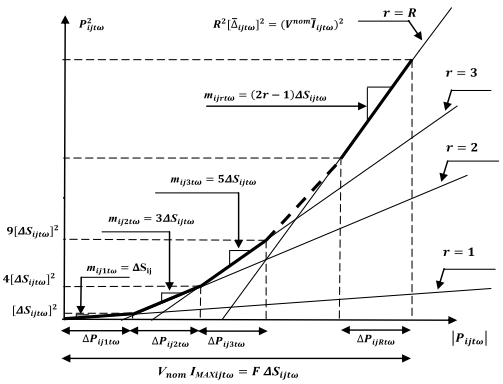


Fig. 6. Modeling the piecewise linear function $P^2_{ijt\omega}$.

The upper and lower voltage limits of the buses are 1.1 and 0.9 pu, respectively. The islanding duration considered is 1 h.

Demand data, recorded every 10 min, is collected from the Iberian Electricity Market [38]. Wind generation data are taken from historical records having 10 min time step. On these bases, the islanding duration is divided into 10-min time intervals (6 time intervals). In the PWL procedure described in Section 3.3, 20 discrete blocks are considered.

Three levels of wind generation are combined with 3 levels of demand to create 9 cases. Accordingly, for demand, 20%, 100% and 180% of the average values from historical data are defined as different levels. For wind power, $N_W = 50$ scenarios are constructed and three wind power levels (low, medium and high) are defined as indicated in the last part of Section 2.1. Furthermore, for a better analysis, two different case studies are considered: (A) only wind generation and (B) wind generation along with storage units. The combination of different levels of power for wind generation and demand produces 9 cases. Consequently, every case is applied for both case studies in order to find out the behavior of the network and analyze various results. The capacity of each storage unit is 0.15 MW and the initial energy level is set to 50% of their capacities (0.075 MW). Also, the upper and lower bounds of storage/production in each storage system are 0.15 MW and 0 MW, respectively.

Table 1
Network characteristics considering three islands (kW).

Island	1st	2nd	3rd	Total
Average demand (20%)	6.04	71.03	143.79	220.86
Average demand (100%)	30.19	355.19	718.95	1104.33
Average demand (180%)	54.35	639.34	1294.12	1987.81
Average low wind level	39.98	79.97	79.97	199.92
Average med wind level	122.75	245.51	245.51	613.77
Average high wind level	263.54	527.07	527.07	1317.68
Storage capacity	75	150	75	300
Number of switches	0	4	1	5

5. Results and discussion

For the 9 cases defined, Tables 2–4 represent the results of the optimization problem considering different cases under islanding conditions for islands 1, 2 and 3, respectively. The initial load and generation for each case before being disconnected from the external grid are shown in the first section of the tables. The results, including connected loads and generators, stored/produced energy and power losses, are illustrated in the remaining two sections of each table, showing the islanded area results in presence of ESS and the results without ESS, respectively.

Since the only energy source under islanding conditions is wind, there are three possibilities: (1) wind generation higher than demand, (2) demand higher than wind and, (3) balanced wind and demand. As the network is analyzed with and without ESS, several situations and conditions are expected.

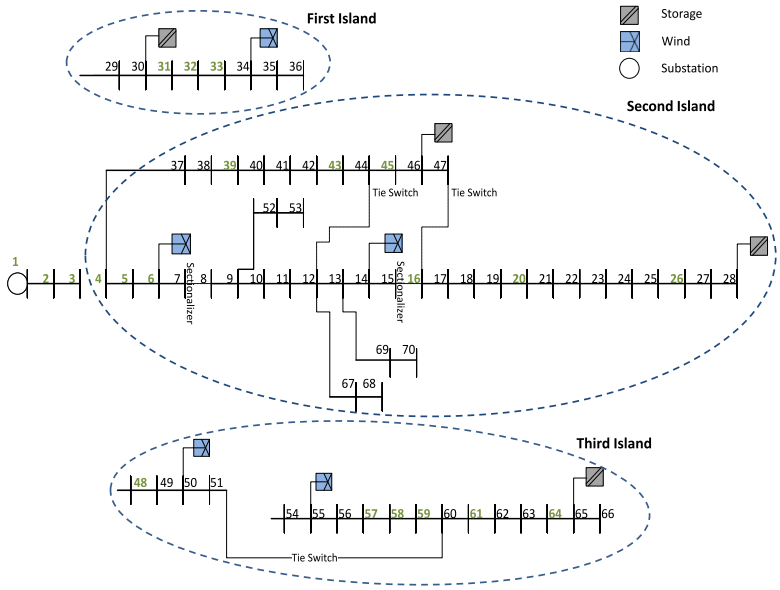


Fig. 7. Network and island configurations.

Table 2
Island 1 results (values in kW).

Island 1 (cases)		1	2	3	4	5	6	7	8	9
Total initial load		6.04	30.19	54.35	6.04	30.19	54.35	6.04	30.19	54.35
Total initial generation		39.98	39.98	39.98	122.75	122.75	122.75	263.54	263.54	263.54
Islanding without ESS										
Load		5.60	24.82	33.47	5.80	28.56	50.93	6.04	30.19	54.35
Generation (wind)		5.95	25.94	34.21	6.16	30.31	54.02	6.41	32.06	57.72
Power losses		0.35	1.12	0.74	0.36	1.74	3.09	0.37	1.87	3.37
Islanding with ESS										
Load		6.04	30.19	54.35	6.04	30.19	54.35	6.04	30.19	54.35
Generation (wind)		38.84	39.98	39.98	75.78	91.89	104.73	79.30	133.39	127.20
Storage	Produces	0.13	3.81	18.08	0.24	1.63	3.42	0.36	1.78	3.20
	Stores	32.74	13.09	3.46	67.56	60.64	51.00	70.59	70.59	70.40
Power losses		0.19	0.51	0.26	2.42	2.69	2.80	3.03	4.38	5.65

Table 3
Island 2 results (values in kW).

Island 2 (cases)		1	2	3	4	5	6	7	8	9
Total initial load		71.04	355.19	639.35	71.04	355.19	639.35	71.04	355.19	639.35
Total initial generation		79.97	79.97	79.97	245.51	245.51	245.51	527.07	527.07	527.07
Islanding without ESS										
Load		55.12	79.90	79.92	66.17	235.23	245.17	71.04	329.29	524.24
Generation (wind)		58.61	79.97	79.97	72.36	239.18	245.51	72.07	331.52	527.07
Power losses		3.49	0.07	0.04	6.18	3.94	0.34	1.03	2.23	2.83
Islanding with ESS										
Load		71.04	229.71	229.93	71.04	333.86	395.22	71.04	355.19	616.47
Generation (wind)		79.97	79.97	79.97	94.56	245.51	245.51	220.46	429.02	527.07
Storage	Produces	15.61	150	150	29.74	100.14	150	0	58.32	92.66
	Stores	24.33	0	0	49.23	9.57	0	148.44	130.92	0.87
Power losses		0.21	0.25	0.04	4.03	2.21	0.29	0.98	1.23	2.39

Table 4
Island 3 results (values in kW).

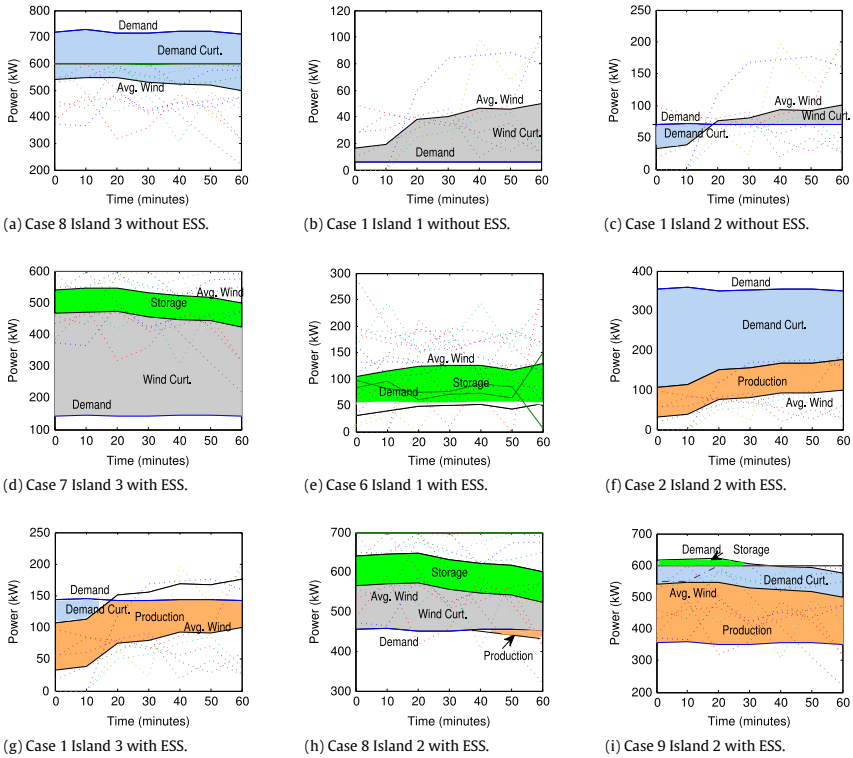
Island 3 (cases)		1	2	3	4	5	6	7	8	9
Total initial load		143.79	718.96	1294.12	143.79	718.96	1294.12	143.79	718.96	1294.12
Total initial generation		79.97	79.97	79.97	245.51	245.51	245.51	527.07	527.07	527.07
Islanding without ESS										
Load		71.93	79.61	79.77	127.70	241.43	242.46	143.11	511.65	512.18
Generation (wind)		73.37	79.97	79.97	135.92	245.51	245.51	151.15	527.07	527.07
Power losses		1.44	0.36	0.20	8.22	4.08	3.05	8.04	15.43	14.89
Islanding with ESS										
Load		143.79	154.76	154.86	134.16	318.23	318.73	143.74	587.81	594.41
Generation (wind)		79.97	79.97	79.97	184.9	245.51	245.51	230.89	523.36	527.07
Storage	Produces	71.34	75	75	5.03	75	75	0	75	75
	Stores	3.66	0	0	49.68	0	0	75	0	0
Power losses		3.85	0.20	0.11	6.09	2.27	1.78	12.15	10.54	7.66

5.1. Islanding without ESS

In the case of islanding without ESS, if the amount of load is higher than generation, the optimization procedure disconnects part of the load in order to keep the real power imbalance within acceptable limits (Fig. 8(a)). Also, with a surplus of generation, the optimization model tries to balance the power in the islanded area by decreasing power generation in that area (Fig. 8(b)). In a few cases, the power imbalance between load and generation is very low and depends on the stochastic inputs of the load and generation, the optimization model tries to shed both of them. This happens mostly in cases 2, island 1 and in cases 1, 5, 8 and 9, island 2, as it can be seen in Table 3 and in case 1, shown in Fig. 8(c).

5.2. Islanding with ESS

In the presence of both wind and storage, several situations are likely to happen in the case of islanding. With an excess of wind generation in the islanded area, three different situations can occur. The first situation occurs when wind generation is higher than the load plus the total storage capacity (Fig. 8(d)). In this case, wind curtailment is unavoidable in every interval and the ESS is fully charged. The second situation occurs when the surplus of generation can be completely stored by the ESS in one hour, thus, avoiding any curtailment. This is the same situation seen in Fig. 8(b), but considering ESS to store the excess of wind generation. However, in the third situation, it may be necessary to disconnect generation in some time intervals due to



(a) Case 8 Island 3 without ESS. (b) Case 1 Island 1 without ESS. (c) Case 1 Island 2 without ESS.

(d) Case 7 Island 3 with ESS. (e) Case 6 Island 1 with ESS. (f) Case 2 Island 2 with ESS.

(g) Case 1 Island 3 with ESS. (h) Case 8 Island 2 with ESS. (i) Case 9 Island 2 with ESS.

Fig. 8. Islanding power balance situations; (Blue: demand curtailment; Gray: wind curtailment; Green: energy storage for ESS; Orange: energy production for ESS). The dashed lines represent the wind scenarios for the corresponding wind level. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

extra generation in that time interval (Fig. 8(e)) i.e., for that 10 min interval, the storage capacity of the ESS is lower than generation and, within this time interval, it is not possible to store energy.

On the other hand, several situations can be analyzed in the case of an excess of demand. In several cases, generally in islands 2 and 3, the total stored energy in ESS is used to compensate the imbalance of power in islanding conditions. However, some loads should be disconnected in order to balance the power (Fig. 8(f) and (g)). In other cases, the ESS injects part of its capacity into the network, which is enough to compensate the power in that area, avoiding any demand curtailment (case 8 in island 3 with ESS) and it is similar to Fig. 8(a), in which the deficit of wind power generation is compensated by the storage production.

Finally, other situations can occur depending on the amount of imbalance between load and generation and the capacity of the ESS. For instance, in cases 8 and 9 of island 2, the ESS produces or stores energy depending on the time interval (Fig. 8(h) and (i)).

5.3. General islanding analysis

Table 2 shows the results of the optimization problem after the disconnection of island 1. The minimum and maximum initial power imbalances in this area are 9.79 kW and 257.5 kW, respectively.

The output of the optimization model for island 2 is illustrated in Table 3. The minimum and maximum initial power imbalances are 8.93 kW and 559.38 kW and they are related to cases 1 and 3, respectively. Unlike other islands, two ESS with a total capacity of 150 kW are connected to this area. In cases 2, 3 and 6 the energy is fully produced by the ESS. On the other hand, only in case 7, the energy is completely stored by the ESS. Noteworthy, in cases 1, 5, 8 and 9, the energy is stored or produced by the ESS depending on the level of wind power or demand in the time intervals. The minimum and maximum power losses are 0.04 kW and 6.18 kW, respectively, and they are related to cases 3 and 4, respectively.

Finally, Table 4 presents the results of the optimization model for island 3. The minimum and maximum initial power imbalances are 63.14 kW in case 1 and 1214.15 kW in case 3, respectively. This islanded area has the highest level of power imbalance in case 3 compared with the other islanded areas. Consequently, the ESS will be fully charged or discharged regarding the amount of power imbalance in the islanded area. Although, in some cases, the energy can be stored or produced by the ESS completely, a small part of generation or demand is disconnected and the ESS cannot avoid disconnecting them. As the reactive power is not compensated by the ESS, in some cases, e.g. cases (1 and 4) a curtailment of generation or demand is unavoidable. Finally, the minimum and maximum power losses are 0.11 kW in case 3 and 15.43 kW in case 8, respectively.

In general, generation and demand curtailment are lower in the presence of ESS in islanded areas. Since power losses are related to the location of load and generation and the limitation of the connection lines in EDS, lower power losses with ESS are not guaranteed.

Regarding the reactive power imbalance in the network, in all cases and islanded areas, the generation is able to compensate the reactive power after islanding and the optimization procedure.

Table 5
Order of complexity.

	Without ESS	With ESS
Binary variables	$4N_B\,N_T\,N_W + N_B$	$4N_B\,N_T\,N_W + 2N_N\,N_T\,N_W + N_B$
Continuous variables	$8N_B\,N_T\,N_W + 10N_N\,N_T\,N_W$	$8N_B\,N_T\,N_W + 12N_N\,N_T\,N_W$
Constraints	$19N_B\,N_T\,N_W + 11N_N\,N_T\,N_W$	$19N_B\,N_T\,N_W + 17N_N\,N_T\,N_W$

Table 6
Order of complexity using binary variables in the PWL.

	Without ESS	With ESS
Binary variables	$4N_B\,N_T\,N_W + N_B + 2N_B\,N_R\,N_T\,N_W$	$4N_B\,N_T\,N_W + 2N_N\,N_T\,N_W + N_B + 2N_B\,N_R\,N_T\,N_W$

Reactive power is introduced as a constraint in the optimization model and power losses are lower than the optimization model including reactive power in the objective function.

5.4. Scalability of the model

All the cases have been solved using MATLAB R2012a [39] and CPLEX under GAMS 24.0 [40] on a Windows 8-based Dell Server R920 with four processors Intel Xeon E7-4820 clocking at 2 GHz and 128 GB of RAM. Table 6 illustrates the comparison between the order of complexity of the model with and without ESS. The number of binary and continuous variables and constraints depends on the number of nodes (N_N), the number of branches (N_B), the number of time intervals (N_T) and the number of scenarios (N_W). In Table 5, the characterization of the model is illustrated.

6. Conclusion

In this paper, a two-stage stochastic MILP reconfiguration model considering wind energy and ESS in EDS has been implemented in order to maximize load and generation under islanded conditions. The objective function of the optimization model has been based on real power with additional constraints for reactive power in the islanded area. The output of the mathematical model has been analyzed by using 9 cases in 3 islanded areas including wind generation and ESS. The proposed model leads to correct operation of the grid in islanded situations and avoids a complete blackout in these areas under different levels of generation and demand. The EDS network has been analyzed by considering wind generation only and with a combination of wind and ESS are analyzed. It has been observed that the combination of wind generation and ESS leads to keeping more load and generation on-line under islanded conditions.

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Appendix. PWL process

The implementation of the PWL within an optimization framework generally requires binary integer variables to enforce adjacency conditions for the piecewise linear segments. Adjacency conditions ensure that $P_{ijrt\omega} \geq 0$ if $P_{ij(r-1)t\omega} = \Delta S_{ijrt\omega}$.

However, omitting binary variables and relaxing the adjacency condition provide a strictly continuous linear approximation of $P^2_{ijt\omega}$ and $Q^2_{ijt\omega}$ that is equivalent to a bounded convex relaxation of (28) as in (43). The adjacency of the power blocks does not need to be enforced explicitly as in [41,42]. It has been verified that (43) is active in the solution.

$$V^2_{it\omega} I^2_{ijt\omega} \geq P^2_{ijt\omega} + Q^2_{ijt\omega}. \tag{43}$$

The proof, as mentioned in [43], is that the function $P^2_{ijt\omega}$ is strictly convex (is the same for $Q^2_{ijt\omega}$) if the Hessian is positive definite ($\nabla^2(P^2_{ijt\omega}) \geq 0$), which is the case.

All of this has been checked experimentally by including binary variables, and the solution has not changed. Yet, by introducing binary variables the computational time increases. This increase has been expressed by determining the computational complexity of the models, as follows, by using the variables already introduced in this paper and adding the number of blocks, N_R, as seen in Table 6.

For the sake of completeness, in order to show the use of binary variables, the new equations that include binary variables are presented as done in [44].

$$\Delta P_{ijrt\omega} \leq \Delta P_{ij(r-1)t\omega} \tag{44}$$

$$\Delta S_{ijrt\omega} - \Delta P_{ij(r-1)t\omega} \leq \mu_{ij(r-1)t\omega} \Delta S_{ijrt\omega} \tag{45}$$

$$\Delta P_{ijrt\omega} \leq (1 - \mu_{ij(r-1)t\omega}) \Delta S_{ijrt\omega} \tag{46}$$

$$\Delta Q_{ijrt\omega} \leq \Delta Q_{ij(r-1)t\omega} \tag{47}$$

$$\Delta S_{ijrt\omega} - \Delta Q_{ij(r-1)t\omega} \leq \eta_{ij(r-1)t\omega} \Delta S_{ijrt\omega} \tag{48}$$

$$\Delta Q_{ijrt\omega} \leq (1 - \eta_{ij(r-1)t\omega}) \Delta S_{ijrt\omega} \tag{49}$$

where $\mu_{ijrt\omega}$ and $\eta_{ij(r-1)t\omega}$ are the binary variables that indicate if the block is filled (0) or not (1).

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Chapter 4

Optimal Placement of Energy Storage and Wind Power under Uncertainty

energies

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Optimal Placement of Energy Storage and Wind Power under Uncertainty

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Abstract: Due to the rapid growth in the amount of wind energy connected to distribution grids, they are exposed to higher network constraints, which poses additional challenges to system operation. Based on regulation, the system operator has the right to curtail wind energy in order to avoid any violation of system constraints. Energy storage systems (ESS) are considered to be a viable solution to solve this problem. The aim of this paper is to provide the best locations of both ESS and wind power by optimizing distribution system costs taking into account network constraints and the uncertainty associated to the nature of wind, load and price. To do that, we use a mixed integer linear programming (MILP) approach consisting of loss reduction, voltage improvement and minimization of generation costs. An alternative current (AC) linear optimal power flow (OPF), which employs binary variables to define the location of the generation, is implemented. The proposed stochastic MILP approach has been applied to the IEEE 69-bus distribution network and the results show the performance of the model under different values of installed capacities of ESS and wind power.

Keywords: optimal location; energy storage systems (ESS); mixed integer linear programming (MILP); wind power; optimal power flow (OPF)

1. Introduction

Government efforts and regulatory agencies have been highly committed to increasing the penetration of renewable energy sources (RES) in distribution networks in order to achieve targets mainly related to emission reduction and fossil energy independence [1]. Wind power capacity has expanded rapidly in the last years, and it has become the most relevant RES in the world. On the other hand, the penetration of RES, especially wind power, has caused several problems due to its intermittency and uncertainty [2]. However, several types of energy storage systems (ESS) are used in electrical networks to cope with problems such as smoothing the output power of RES [3], improving power system stability [4,5], reducing distribution losses and being economically efficient [6]. Moreover, dispatchable storage technologies provide added benefits for utilities, distributed generation (DG) owners and customers, through reliability, improved power quality, and overall reduced energy costs [7–9]. For these reasons, in the new context of DG uncertainty, the physical placement of both wind and energy storage elements in the system must be studied. Having RES and EES in electrical networks is a challenge to integrate them in an optimal way in distribution networks. Furthermore, in many countries, the target is to increase the installed capacity of renewable energy in distribution grids. This requires the combination of wind and storage units in order to deal properly the system. The models focus on the optimal location of both units and the benefits of combining wind and storage.

Several studies habe been performed for the location of DG. In [10], state-of-the-art models and optimization methods applied to DG placement are reviewed. Optimal placement of DG is done by solving the required objective function, which could be single or multi-objective.

The main single-objective functions include generation cost optimization [11], minimization of system losses [12–14] and voltage stability [15]. The multi-objective formulation is converted to a single-objective function using the weighted sum of individual objectives [16] (active power loss, reactive power loss, voltage profile and reserve capacity).

In addition, several works have described the effectiveness of integrating storage with wind and they have proposed optimal ESS allocation models. Authors in [17] implemented an optimal location for a battery-based ESS to reduce distribution losses. A methodology to allocate energy storage resources in order to decrease wind energy curtailment costs under high wind penetration is used in [18]. In [19], an investor-owned independently-operated storage unit maximizes its profit in the day-ahead market. In [20] the authors formulated an objective function to minimize overall capital cost. Reference [21] used a direct current (DC) optimal power flow (OPF) to minimize the operation cost of the system subject to network constraints. An alternative current (AC) OPF that minimizes operating cost is used in [22]. In [23] the objective function is composed of ESS charging and discharging costs, weighting cost losses and the additional cost of adding more generation. In [24], the objective function comprises the squared norm of voltage deviations of all the network buses over a given period of time, the total amount of network losses over a given period of time and the total energy cost related to the power flow with the external grid.

In terms of methodologies, an analytical method is used in [14], numerical methods such as linear programming (LP) [13], non-linear programming (NLP) [18], mixed-integer non-linear programming (MINLP) [15], and dynamic programming (DP) [3] are developed. Heuristic methods have been also applied, where a genetic algorithm (GA) is applied using chance constrained programming (CCP) [2], tabu-search (TS) [12], particle swarm optimization (PSO) [17], and big bang–big crunch (BB–BC) in [16]. Probabilistic optimal power flow (POPF) models are used in [7,21–24]. In [19] the authors converted the stochastic problem to a convex optimization one.

With the expected growth of wind power penetration in electrical networks, it is necessary to consider the intermittency and uncertainty of these resources. In previous works, [1,3,6,8–14,16,17,19] uncertainty was not taken into account. In other works [4,5], forecasting and prediction methods are applied, respectively. Unlike [18,24], where an auto regressive moving average (ARMA) technique is used to model wind speed, we propose a probabilistic method based on time series for generating scenarios, as in [25].

Table 1 summarizes the main differences between this paper and the state-of-the-art related to the optimal location of units. The table shows whether a particular aspect is considered or not. Moreover, the objective function and the methodology used is mentioned in the table. Other works [3,6–9,21] show the impact and the benefits of combining RES with ESS in distribution networks in an operation framework, assuming some locations as given. The advantage of our approach is that we optimally locate both wind and ESS in a distribution network. This means that a linear AC OPF is used for this purpose and stochasticity is also taken into account. In addition, the objective function includes technical and generation aspects of current distribution grids.

In this paper, we propose a cost-based stochastic operation model to find the optimal location of wind power and storage facilities, which has not been presented yet in technical literature. It is worth mentioning that, due to the intermittency and uncertainty of wind power, the combination of RES and ESS is mainly desirable in terms of reliability, wind curtailment cost and loss reduction. As a result, the motivation of this paper is to show the effect of the joint combination of wind and EES in terms of operating costs, considering different penetration levels of wind power and ESS.

The main contributions of this paper are the following:

(1) Regarding the methodology, a stochastic mixed integer linear programming (MILP) model is introduced to consider the inconsistency and intermittency of renewable power sources, in this case wind power. The MILP method applied provides these benefits:

    (a) The mathematical model is robust.

(b) The computational behavior of a linear solver is more efficient than those of nonlinear solvers, providing a global optimum solution.
(c) Convergence can be guaranteed using classical optimization techniques.

(2) From a modeling perspective, a novel joint RES and EES optimal location model, which has not been done yet, is presented here for a distribution system.

Table 1. Comparison of optimal location models. ESS: energy storage systems; CCP: chance constrained programming; MINLP: mixed-integer non-linear programming; TS: tabu-search; NL: non-linear; AC: alternative current; OPF: optimal power flow; GA: genetic algorithm; POPF: probabilistic optimal power flow; BB-BC: big bang-big crunch; PSO: particle swarm optimization; NLP: non-linear programming; DC: direct current; MILP: mixed integer linear programming.

Approach	Optimal Wind Site	Optimal ESS Site	Stochasticity	Objective Function	Methodology
[2]	√	×	√	Investment, operation, maintenance and losses costs minimization	CCP
[11]	√	×	×	Fuel cost minimization	MINLP
[12]	√	×	×	Power losses minimization	TS
[13]	√	×	×	Power losses minimization	Multiperiod NL AC OPF
[14]	√	×	×	Power losses minimization	Improved analytical method
[15]	√	×	×	Voltage stability margin maximization	MINLP
[16]	√	×	×	Multi-objective optimization (active, reactive power losses, voltage profile and reserve capacity minimization)	BB-BC
[17]	×	√	×	Power losses minimization	PSO
[18]	×	√	×	Wind energy maximization	NLP
[20]	×	√	×	Overall capital cost	Multiperiod NLP AC OPF
[22]	×	√	√	Generation cost minimization	GA POPF
[23]	×	√	√	ESS, transmission losses and conventional generation cost minimization	NLP DC POPF
[24]	×	√	√	Multi-objective optimization (voltage deviation, network losses, energy cost minimization	GA
Proposed approach	√	√	√	Expected value minimization of energy losses, voltage deviation, generation, wind curtailment and storage costs	MILP AC OPF

The main advantage of using LP (in our case, stochastic MILP due to the need of binary variables for optimal location and uncertainty modeling) is that it searches for and guarantees the global optimal solution. The methods shown in Table 1 are either nonlinear or metaheuristic, guaranteeing a local optimum; however, they do not assure that the solution found is the global optimal solution. For this reason, we use MILP to obtain the best solution. As seen in Table 1, in the context of allocation problems, only our work includes a linear model.

The rest of the paper is organized as follows. In Section 2, a stochastic model of wind and a generic model of a storage system are introduced. Section 3 defines the mathematical model formulated as a stochastic MILP. The main results of the case studies are shown in Section 4. Finally, the main conclusions are presented in Section 5.

2. Scenario Generation and Storage Modeling

2.1. Scenario Generation

In the presence of renewable-based DG, it is necessary to consider the intermittency and uncertainty of these resources. Consequently, in order to model wind uncertainty, a probabilistic method based on time series has been implemented. Historical data of one year of wind speed is considered as initial data for candidate areas of wind generation. This section explains the generation of wind scenarios.

For each season, the cumulative distribution function (CDF) of historical wind speed is constructed. In Figure 1a, historical wind speed data for winter is represented. Initially, the number of scenarios is decided. Then, for each scenario, the initial value of wind speed is determined by a random number from a uniform probability distribution (0,1) that enters as the probability of the CDF of the historical data and identifies the corresponding wind value. The CDF of the historical data of winter is illustrated in Figure 1b. This methodology is known as the classical selection mechanism.

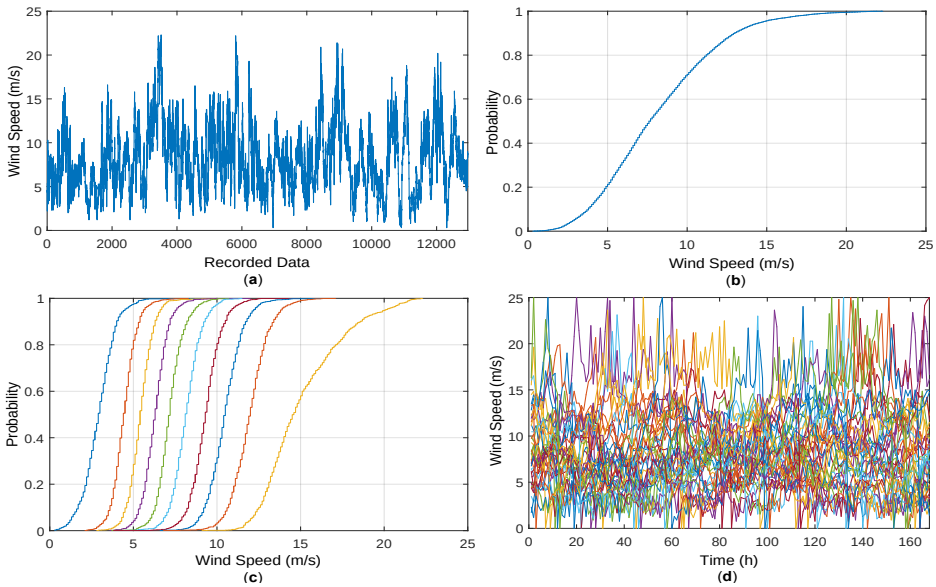

Figure 1. Method for wind scenario generation: (**a**) wind speed data for winter season; (**b**) cumulative distribution curve for winter season; (**c**) cumulative distribution curve for the 10 deciles; and (**d**) wind scenarios.

In order to select the next wind speed value, the CDF of the historical wind speed data has previously been divided into deciles, obtaining the wind speed ranges. For instance, in winter, wind speeds have the following limits: 3.85, 4.98, 5.92, 7, 7.95, 8.81, 9.93, 11.27, 13.08, 22.38 m/s. Taking all the wind speeds located in the same decile, the CDF corresponding to the wind speed of the historical data at the next step is constructed. The decile of the initial wind speed, for each scenario, is identified. The CDF of the wind speed at the next time step for that decile is considered, extracting the wind speed from that CDF with the classical selection mechanism indicated above. The decile of the wind speed extracted is identified, the corresponding CDF of the next time step is considered, the new wind speed is extracted, and this is performed successively until all the wind speed values in the time interval of analysis have been extracted. The CDF corresponding to the wind speed of the historical data at the next step for each decile is visualized in Figure 1c. Finally, wind scenarios are represented for one week in Figure 1d.

The same approach is done for substation prices and load scenarios as seen in Figure 2.

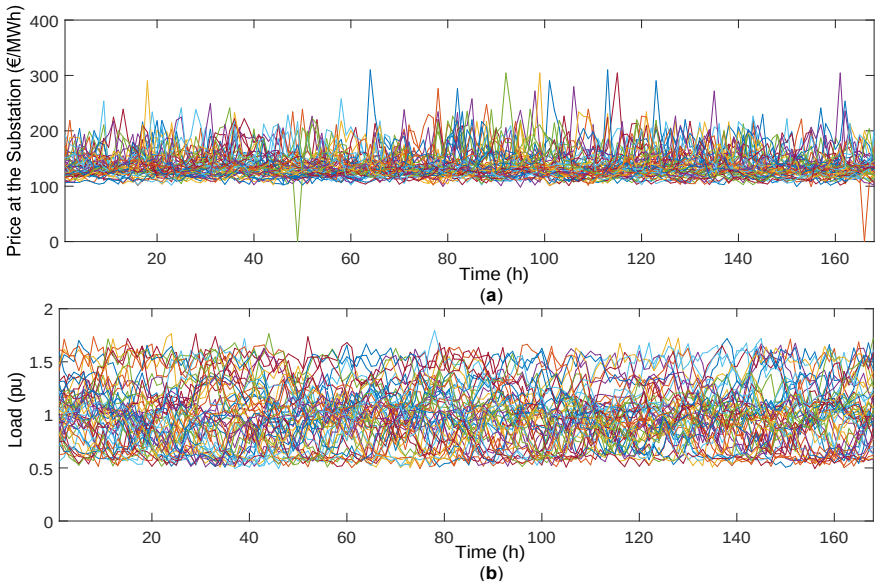

Figure 2. Substation price and load scenarios: (**a**) price at the substation (€/MWh); and (**b**) load (pu).

In order to have a tractable computational time, 50 scenarios have been generated for each input (wind, load, substation price) and they been reduced to four scenarios for each one of the inputs by using the *k*-means clustering algorithm. This method can be used to partition a given set of scenarios into a given number of clusters. As a result of this partition, scenarios with similar features are assigned to the same cluster. The centroid of each cluster represents a somewhat average pattern of all the scenarios included in a cluster. Since the centroid is artificial, the original scenario with the lowest probability distance from the centroid is used to represent the cluster. The relationship between the considered uncertainty sources is graphically described in Figure 3, resulting in 4^3 scenarios. The number of scenarios has been limited to this figure to minimize the dimensionality in the problem formulation.

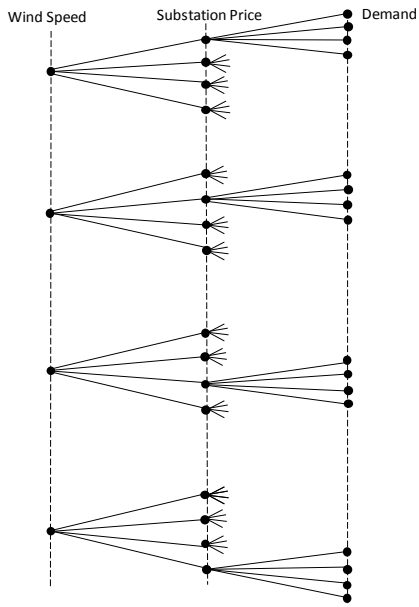

Figure 3. Considered scenario tree for wind power generation, substation price and load.

2.2. Generic Energy Storage Systems Modeling

Recently, the use of storage devices has increased significantly. In this work, an ideal and generic storage unit model is presented as in [26], which is "a device with the capability of transforming and storing energy, and reverting the process by injecting back the stored energy to the system". Within this context, it can be conveniently integrated in complex optimization problems. An ideal and generic storage device is modeled with the hypothesis mentioned below:

- There are no up or down ramps.
- There are no storage energy losses.
- There is no hysteresis in discharging or charging.
- There are conversion losses. This means there are efficiency rates of direct (production) and reverse (storage) energy transformation. These rates are given with respect to the energy measured at the bus connected to the storage unit.
- Production/storage costs are the same for any level of production/storage of the unit.
- Energy production/storage occurs at constant power for the minimum period of study (typically one hour).
- The depth of discharge is assumed to be 80% of the maximum storage energy capacity.

The mathematical formulation of ESS is represented through Equations (1)–(5):

$$\underline{s}_i^{\mathrm{s}}\beta_i \leq s_{it\omega}^{\mathrm{s}} \leq \overline{s}_i^{\mathrm{s}}\beta_i \tag{1}$$

$$\underline{s}_i^{\mathrm{p}}\beta_i \leq s_{it\omega}^{\mathrm{p}} \leq \overline{s}_i^{\mathrm{p}}\beta_i \tag{2}$$

$$\underline{x}_i \leq x_{it\omega} \leq \overline{x}_i \tag{3}$$

$$x_{it\omega} = x_{i(t-1)\omega} + \Delta[\eta_i^{\mathrm{s}} s_{it\omega}^{\mathrm{s}} - (1/\eta_i^{\mathrm{p}}) s_{it\omega}^{\mathrm{p}}] \tag{4}$$

$$x_{it=0\omega} = x_{it=T\omega} \tag{5}$$

In the above equations, the actual storage (charge) and production (injection into the network) bounds are defined in Equations (1) and (2). A binary variable β_i for allocating EES in a node i of the

network is introduced in these equations. Additionally, capacity limits of the ESS are introduced in Equation (3). Equation (4) shows the storage transition function. Thus, the state of charge, $x_{it\omega}$ (storage level at bus i, period t and scenario ω), of the ESS located at bus i at the end of time interval t for each scenario ω depends on the previous state of charge, $x_{i(t-1)\omega}$, and the power storage/production during the current interval. In Equation (5), the initial energy status of the ESS has to be the same as that at the end of the period.

Finally, Equation (6) defines the location of ESS under different penetration levels (total number of EES units) in the model, ESS:

$$\sum_i \beta_i = N^{\mathrm{st}} \tag{6}$$

3. Mixed Integer Linear Programming Formulation

The following assumptions are made to represent a simplified power flow of a distribution system, generation and storage devices:

- The electric distribution system is a balanced three-phase system and can be represented by its equivalent single-phase circuit.
- The time stretch used for the simulation is one week, in intervals of time of 1 h.
- Several candidate buses are selected for the optimal location of the wind unit. The optimal locations, based on wind resources, should be selected according to: high average speed, acceptable diurnal and seasonal variations, acceptable levels of turbulence and extreme winds. Other technical criteria are the softness of the orography for the civil works and the proximity of power lines with evacuation capacity for interconnection, technical feasibility and ease of construction or absence of environmental, urban, archaeological and cultural conditions.
- In the case of locating ESS, all the buses are candidates for location.
- For the sake of simplicity, only one wind power unit and one ESS unit are used. The variation of the installed amount of wind and ESS capacities at the optimal locations is discussed in the case study.

3.1. Objective Function

The aim of the optimization model proposed is to minimize all the costs associated with the operation of a distribution network and how the penetration of DG and ESS affects it. The objective function in Equation (7), the expected values of the total cost of the real power losses and the voltage deviation with respect to the reference value in branch i, j are penalized in Equation (8). The probability-weighted average of all possible values produces the expected values of the costs. Furthermore, the cost of the energy that comes from the substation, wind curtailment cost, and production and storage costs are also included in Equation (9):

$$\min \quad \{E[\psi(\omega)] + E[\kappa(\omega)]\} \tag{7}$$

$$\psi(\omega) = \sum_t \sum_{ij} \Delta R_{ij} I^2_{ijt\omega} C^{\mathrm{loss}} + \sum_t \sum_{ij} \Delta \left| V^2_{it\omega} - V^2_{\mathrm{ref}} \right| C^{V_{\mathrm{dev}}} / R_{\mathrm{nom}} \tag{8}$$

$$\kappa(\omega) = \sum_t \sum_i \Delta [P^{\mathrm{sub}}_{it\omega} C^{\mathrm{sub}}_{it\omega} + s^{\mathrm{p}}_{it\omega} C^{\mathrm{p}} + s^{\mathrm{s}}_{it\omega} C^{\mathrm{s}} + P^{\mathrm{w\_curt}}_{it\omega} C^{\mathrm{w\_curt}}] \tag{9}$$

3.2. Constraints

The objective function is subject to a set of constraints to assure optimal operational conditions.

3.2.1. Power Balance Equations

Real wind power including curtailment is represented in Equation (10). This equation is active in the nodes where the model optimally locates the wind unit, and the active power injected comes from the wind power scenario generation discounting the wind power curtaiment, if necessary. The optimal location of wind power generation at bus i is defined by binary variable α_i:

$$P_{it\omega}^{\text{wind}} = P_{it\omega}^{\text{w\_fore}}\alpha_i - P_{it\omega}^{\text{w\_curt}} \tag{10}$$

$$\sum_i \alpha_i = N^{\text{wind}} \tag{11}$$

Equation (11) defines the location of wind units under N^{wind} different penetration levels of wind.

Real and reactive power balance equations at bus i are formulated in Equations (12) and (13). For both active and reactive power, wind power generation, production/storage of ESS, and the power flow from/to the substation are considered:

$$P_{it\omega}^{\text{sub}} + P_{it\omega}^{\text{wind}} + \sum_{\text{k}} (P_{\text{k}it\omega}^{+} - P_{\text{k}it\omega}^{-}) - \sum_j [(P_{ijt\omega}^{+} - P_{ijt\omega}^{-}) + R_{ij} I_{ijt\omega}^2] + (s_{it\omega}^{\text{p}} - s_{it\omega}^{\text{s}}) = P_{it\omega}^{\text{dem}} \tag{12}$$

$$Q_{it\omega}^{\text{sub}} + Q_{it\omega}^{\text{wind}} + \sum_{\text{k}} (Q_{\text{k}it\omega}^{+} - Q_{\text{k}it\omega}^{-}) - \sum_j [(Q_{ijt\omega}^{+} - Q_{ijt\omega}^{-}) + X_{ij} I_{ijt\omega}^2] = Q_{it\omega}^{\text{dem}} \tag{13}$$

In order to distinguish the direction (sense) of the current and power flow (forward or downward the substation) due to existence of DG, especially in Equations (12) and (13), two types of positive separate variables are used for both active ($P_{ijt\omega}^{+}$, $P_{ijt\omega}^{-}$) and reactive power ($Q_{ijt\omega}^{+}$, $Q_{ijt\omega}^{-}$), as seen in Figure 4.

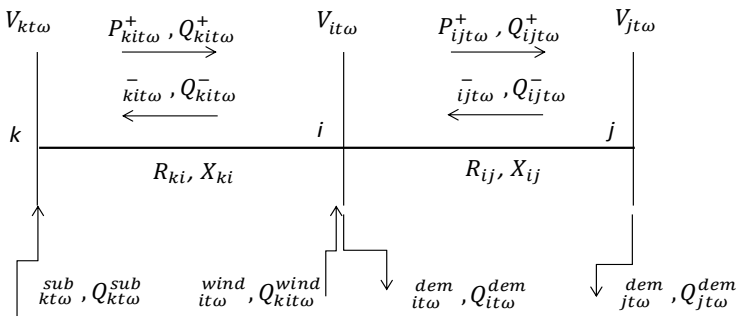

Figure 4. Illustrative radial network with DG.

3.2.2. Non-Linear Apparent Power Equations

The current flow magnitude calculation is expressed by Equation (14), which is the only non-linear equation in the optimization model. The linearization procedure is explained in detail in Section 3.3:

$$V_{jt\omega}^2 I_{ijt\omega}^2 = P_{ijt\omega}^2 + Q_{ijt\omega}^2 \tag{14}$$

3.2.3. Voltage Drop Equations

Voltage drops between buses are formulated in Equation (15):

$$V_{it\omega}^2 - Z_{ij}^2 I_{ijt\omega}^2 - 2[R_{ij}(P_{ijt\omega}^+ - P_{ijt\omega}^-) + X_{ij}(Q_{ijt\omega}^+ - Q_{ijt\omega}^-)] - V_{jt\omega}^2 = 0 \tag{15}$$

The equation above is obtained from the initial phasor equation in Equation (16):

$$\vec{V}_i - \vec{V}_j = \vec{I}_{ij}(R_{ij} + jX_{ij}) \tag{16}$$

The complex power expressed by the product that appears in Equation (17), where $\vec{V}_i$,$\vec{V}_j$,$\vec{I}_{ij}$ are voltages and currents, and $\vec{I}_{ij}^*$ is the complex conjugate of the current:

$$\vec{V}_j \vec{I}_{ij}^* = P_{ij} + jQ_{ij} \tag{17}$$

Substituting the current magnitude value of Equation (17) into Equation (16) leads to Equation (18):

$$\vec{V}_i - \vec{V}_j = (P_{ij} + jQ_{ij}/\vec{V}_j)^*(R_{ij} + jX_{ij}) \tag{18}$$

By operating, this leads to Equation (19), where $\vec{V}_i$ is equal to its module V_i and its phasor θ_i, and $\theta_{ij} = \theta_i - \theta_j$, obtaining Equation (20):

$$(\vec{V}_i - \vec{V}_j)\vec{V}_j^{\,*} = (P_{ij} - jQ_{ij})(R_{ij} + jX_{ij}) \tag{19}$$

$$V_i V_j(\cos(\theta_{ij}) + j\sin(\theta_{ij})) = (P_{ij} - jQ_{ij})(R_{ij} + jX_{ij}) \tag{20}$$

Separating the real Equation (21) and imaginary parts Equation (22), we obtain:

$$V_i V_j \cos(\theta_{ij}) = P_{ij}R_{ij} + Q_{ij}X_{ij} + V_j^2 \tag{21}$$

$$V_i V_j \sin(\theta_{ij}) = P_{ij}X_{ij} - Q_{ij}R_{ij} \tag{22}$$

Considering the relation $Z_{ij}^2 = R_{ij}^2 + X_{ij}^2$ and the trigonometric rule $\sin\theta_{ij}^2 + \cos\theta_{ij}^2 = 1$, and summing the squares of Equations (21) and (22), we obtain the expression of the voltage drop:

$$V_i^2 - Z_{ij}^2 I_{ij}^2 - 2[R_{ij}P_{ij} + X_{ij}Q_{ij}] - V_j^2 = 0 \tag{23}$$

Specifying Equation (23) in the model, with the inclusion of the direction of the power flow, this becomes Equation (15). Finally, the maximum and minimum voltage variations for bus *i* are defined in Equation (24):

$$\underline{V}^2 \leq V_{it\omega}^2 \leq \overline{V}^2 \tag{24}$$

3.2.4. Current and Power Magnitude Limits

Regarding thermal limits, a set of constraints is introduced for current in Equation (25), real power in Equations (26) and (27), and reactive power in Equations (28) and (29) limits, respectively. In addition, Equations (30) and (31) are set to avoid considering forward and backward power flows simultaneously. Note that Equations (26)–(29) are auxiliary constraints to improve the convergence of the proposed model:

$$0 \leq I_{ijt\omega}^2 \leq \overline{I}_{ij}^2 \tag{25}$$

$$P_{jit\omega}^{+} \leq V_{\text{nom}} \overline{I}_{ij} v_{ijt\omega}^{P^+} \tag{26}$$

$$P_{jit\omega}^{-} \leq V_{\text{nom}} \overline{I}_{ij} v_{ijt\omega}^{P^-} \tag{27}$$

$$Q_{jit\omega}^{+} \leq V_{\text{nom}} \overline{I}_{ij} v_{ijt\omega}^{Q^+} \tag{28}$$

$$Q_{jit\omega}^{-} \leq V_{\text{nom}} \overline{I}_{ij} v_{ijt\omega}^{Q^-} \tag{29}$$

$$v_{ijt\omega}^{P^+} + v_{ijt\omega}^{P^-} \leq 1 \tag{30}$$

$$v_{ijt\omega}^{Q^+} + v_{ijt\omega}^{Q^-} \leq 1 \tag{31}$$

3.2.5. Wind Reactive Power Equations

In order to coordinate real and reactive power, the limitations of reactive power for wind units are calculated in Equations (32)–(34):

$$Q_{it\omega}^{\text{wind}^-} = P_{it\omega}^{\text{wind}} (\tan(\arccos(-PF_i^{\text{wind}}))) \tag{32}$$

$$Q_{it\omega}^{\text{wind}^+} = P_{it\omega}^{\text{wind}} (\tan(\arccos(PF_i^{\text{wind}}))) \tag{33}$$

$$Q_{it\omega}^{\text{wind}^-} \leq Q_{it\omega}^{\text{wind}} \leq Q_{it\omega}^{\text{wind}^+} \tag{34}$$

3.3. Linearization Procedure

To create a linear equation from constraint Equation (14), the two sides of the equation should be managed separately. Note that $V_{it\omega}^2$ and $I_{ijt\omega}^2$ are variables that represent the square magnitude values of voltage and current, respectively, and they are used in Equations (12)–(25).The linearization process of Equation (14) is stated below.

- $V_{jt\omega}^2 I_{ijt\omega}^2$: the left side of Equation (14) is handled by dividing $V_{jt\omega}^2$ into small segments. Nevertheless, this leads to an increase in the number of binary variables and computation time. In distribution systems, voltage magnitudes are within a small range, so a constant value V_{ref}^2 can be approximated as the voltage magnitude for the first run of the model, in which binary variables are relaxed [27], as seen in Equation (35):

$$V_{jt\omega}^2 I_{ijt\omega}^2 \approx V_{\text{nom}}^2 I_{ijt\omega}^2 \tag{35}$$

  Next, the model is run again and $V_{jt\omega}^2$ takes the value resulting from the first run. Note that $V_{jt\omega}^2$ hardly changes after the second run. Because of the limited range of voltage magnitude variation, this simplification has a small error.
- $P_{ijt\omega}^2 + Q_{ijt\omega}^2$: both terms on the right side of (Equation (14)) are handled by introducing a piecewise linear approximation [28]. The linearization process is the following:

$$P_{ijt\omega}^2 + Q_{ijt\omega}^2 = \sum_r (m_{ijrt\omega}\Delta P_{ijrt\omega}) + \sum_r (m_{ijrt\omega}\Delta Q_{ijt\omega}) \quad (36)$$

$$P_{ijt\omega}^+ + P_{ijt\omega}^- = \sum_r \Delta P_{ijrt\omega} \quad (37)$$

$$Q_{ijt\omega}^+ + Q_{ijt\omega}^- = \sum_r \Delta Q_{ijrt\omega} \quad (38)$$

$$0 \le \Delta P_{ijrt\omega} \le \Delta S_{ijrt\omega} \quad (39)$$

$$0 \le \Delta Q_{ijrt\omega} \le \Delta S_{ijrt\omega} \quad (40)$$

where:

$$m_{ijrt\omega} = (2r-1)\Delta S_{ijrt\omega} \quad (41)$$

$$\Delta S_{ijrt\omega} = (V_{\text{nom}}\bar{I}_{ij})/R_{ij} \quad (42)$$

Equation (36) is a piecewise linear approximation of $(P_{ijt\omega}^2 + Q_{ijt\omega}^2)$, and Equations (37) and (38) represent that $(P_{ijt\omega}^+ + P_{ijt\omega}^-)$ and $(Q_{ijt\omega}^+ + Q_{ijt\omega}^-)$ are equal to the sum of the values in each block of the discretization, which means they are a set of linear terms. In addition, $m_{ijrt\omega}$ and $\Delta S_{ijrt\omega}$ are constant parameters, and Equations (37) and (38) are linear expressions. Thus, Equation (43) represents the final linear form of constraint in Equation (14). In this equation, $V_{jt\omega}^2$ is a parameter and $\sum_r (m_{ijrt\omega}\Delta P_{ijrt\omega})$ and $\sum_r (m_{ijrt\omega}\Delta Q_{ijrt\omega})$ are linear. The linearization of the active power Equation (14) is shown in Figure 5:

$$V_{\text{ref}}^2 I_{ijt\omega}^2 = \sum_r (m_{ijrt\omega}\Delta P_{ijrt\omega}) + \sum_r (m_{ijrt\omega}\Delta Q_{ijrt\omega}) \quad (43)$$

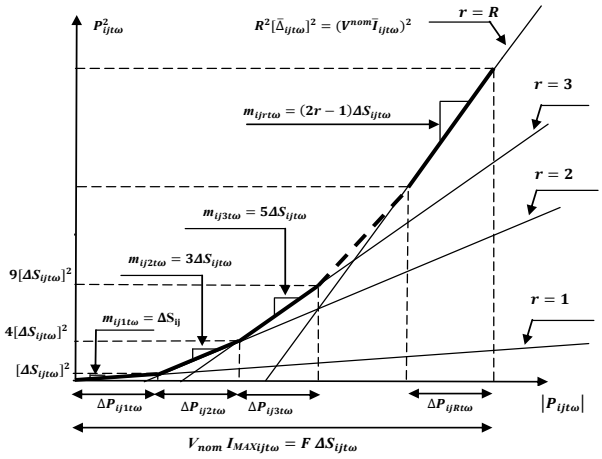

Figure 5. Modeling piecewise linear function $P_{ijt\omega}^2$.

4. Case Studies

4.1. Network Overview

The network used for the optimal location of both wind generation and ESS is the IEEE 69-bus system shown in Figure 6, where the bus numbers in blue are buses that are not connected to loads (as in [29]) and the candidate buses for both wind and ESS are represented. The maximum current flow through the branches is 150 A and network parameters are given in [29]. Since the voltage values vary through iterations, the voltage range is between 1.1 pu and 0.9 pu. In the linearization, 20 discrete blocks are considered since the solutions hardly change from 20 blocks onwards in the piecewise linearization procedure.

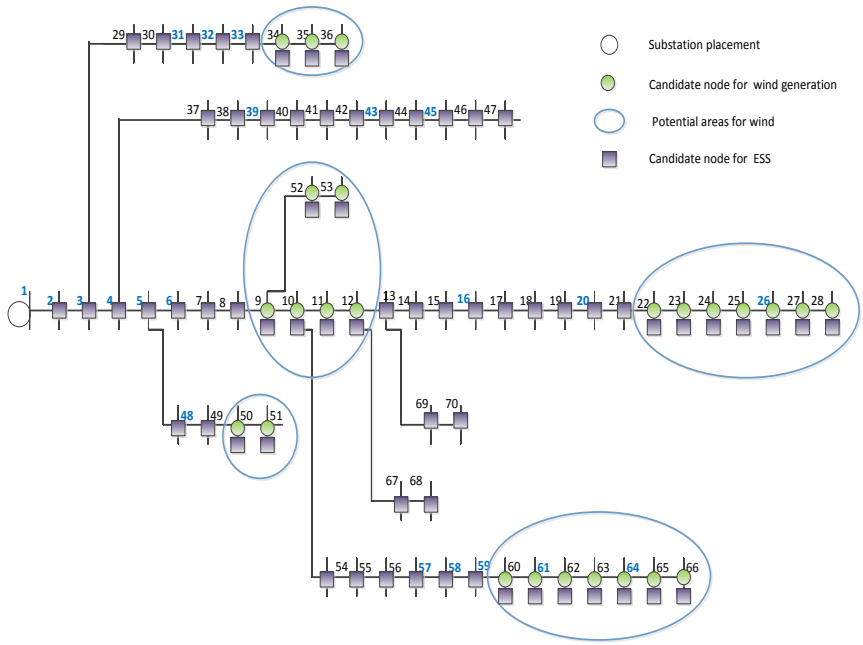

Figure 6. 69-bus network topology.

In order to generate scenarios, explained in Section 2.1, historical data of one year of wind speed is considered as initial data [30] and historical load values and generation prices are collected every hour from the Iberian Electricity Market for the extrapeninsular electric system Majorca-Menorca [31] for one year. The costs of power losses, voltage deviation and wind curtailment, production of the storage (discharging) and storage (charging) cost are \$15/MWh, \$15/MWh and \$500/MWh.

The base power is 1 MVA and the installed power for wind generation can be either 1000 kW or 1500 kW for the different cases. The generic energy storage unit [32] can have different energy capacities: 500 kWh, 1000 kWh, and 1500 kWh, where the maximum storage/production power ranges between 100 kW and 1200 kW. The minimum storage/production power is set to 0. The initial energy level is set to 50% of its capacity. The efficiency rates to store or produce are set to 85%. The costs of production of the storage (discharging) and storage (charging) \$0.1/MWh and \$0.5/MWh, as in [25,26,28].

4.2. Simulation Results

This section shows the optimal location buses and describes the results of the operating costs: losses of the distribution network, substation, energy storage/production, wind curtailment and the voltage for selected cases studies. Different installed power/capacity levels of one wind unit and 1 EES unit are analyzed in the following independent cases, including a case without any unit (Case 1) and another with only high penetration of wind (Case 10), as seen in Table 2.

Table 2. Characterization of the different case studies.

Values (pu)	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10
Wind Power	0	1	1	1	1	1.5	1.5	1.5	1.5	1.5
ESS Capacity	0	0.5	0.5	1	1	1	1	1.5	1.5	0
ESS Max Power	0	0.1	0.4	0.2	0.8	0.2	0.8	0.3	1.2	0

The optimal locations, in which binary variables (α_i and β_i) are active, are obtained for the different case studies as seen in Table 3.

Table 3. Optimal location of wind generation and storage generation.

Cases	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10
Wind Location	-	62	62	62	62	62	62	62	62	62
ESS Location	-	62	62	62	62	9	9	62	62	-

It can be seen that, in all the cases studies, the location of wind generation is at bus 62, which has the highest demand of the system. Thus, basically, the wind power production feeds that bus and the excess is provided to the network to feed the loads nearby or being stored in the ESS. Mainly, the storage device is co-located at the same bus, except for the cases in which the storage value is 1 pu and wind power is 1.5 pu, resulting in its placement at bus 9.

As seen in Table 4, increasing the capacity of wind generation significantly decreases the production cost of the network for one week. Network losses are also reduced if the installed wind capacity is 1 pu. However, considering a high installed capacity of wind, real power losses are increased, as seen in Cases 6–10.

Table 4. The model solution for all the cases.

Costs ($)	Case 1	Case 2	Case 3	Case 4	Case 5
Total	27,170	14,294	14,236	14,193	14,118
Voltage	120	70	71	70	72
Losses	147	110	102	102	95
Substation	26,902	14,114	14,063	14,021	13,951
Wind curtailment	-	-	-	-	-
Discharging	-	0.85	1.89	1.49	2.64
Charging	-	1.04	2.34	1.84	3.26
Costs ($)	**Case 6**	**Case 7**	**Case 8**	**Case 9**	**Case 10**
Total	10,395	10,250	10,121	10,025	15,471
Voltage	59	64	70	69	148
Losses	140	137	112	107	296
Substation	10,196	10,049	9,940	9,849	10,493
Wind curtailment	-	-	-	-	4,534
Discharging	5.34	15.60	5.98	20.68	-
Charging	6.60	19.26	7.38	25.53	-

It is also desirable to have an ESS unit with a high value of maximum production/storage power because the device is less constrained to charge or discharge when it is required by the network. In this case, the cost of the energy that comes from the substation slightly decreases as seen between Cases 2 and 3. It is clear that increasing the installed capacity of storage can benefit the operational cost as it has more capacity to charge or discharge depending on the production cost in that hour (see the difference between Cases 6 and 8, and also Cases 7 and 9). In addition, network losses are decreased when the storage capacity increases from 1 pu to 1.5 pu while voltage deviation is slightly worse.

The behavior of storage depends on whether it is charging or discharging. Storage absorbs the excess of wind in periods when it exceeds the total load of the system. In other situations in which there is high wind and high load, ESS can also absorb energy in order not to violate the technical constraints of the distribution network. The ESS injects energy in the network when the production cost of the whole system is more expensive. Furthermore, another advantage of ESS is that they avoid wind power curtailment and its corresponding cost as it happens in Case 10. In this case, there are some hours in which wind generation is higher than load, which means that this power cannot be evacuated as the substation can only import power upstream; however, it cannot export power upstream. In the new context of increasing renewable energy in networks, ESS is a key element to deal with these situations and avoid wind curtailment. In addition, the effect of increasing the maximum power of the ESS for the same energy capacity, as seen in Case 7 with respect to Case 6, is that the ESS charges and discharges much more than in Case 6. This also reduces the injection from the substation and the overall costs making it a more flexible system that can react to the stochasticity of wind production.

Figure 7 shows the behavior of storage for some of the scenarios. The initial and final levels of energy in the ESS are equal to 0.75. It is observed that, depending on the value of wind power and demand in the distribution system at a certain hour, the behavior of storage is different. At the beginning of the time horizon, wind power is at its maximum level, so the ESS is charged up to hour 22, except for the hours when demand slightly increases (hour 4), in which the ESS discharges a bit without the need for the substation to supply. After hour 22, wind generation decreases, thus the ESS produces during the hours when the drop in wind production is more pronounced. At hour 52, the ESS discharges until its minimum value is reached, 0.3 pu, as we assumed a depth of discharge of 80% of the maximum ESS capacity (1.5 pu in this case), remaining at this value later on. This is a consequence of having low wind and a demand increase. In this situation, the substation begins to inject power into the network, as wind remains low. After that, wind production increases again (hour 96) and the ESS stores energy, meanwhile the substation decreases its injection until reaching 0 again. To sum up, under high wind, the ESS charges sharply if the demand is low and slightly if the demand is medium. It injects power at low wind levels and high demand.

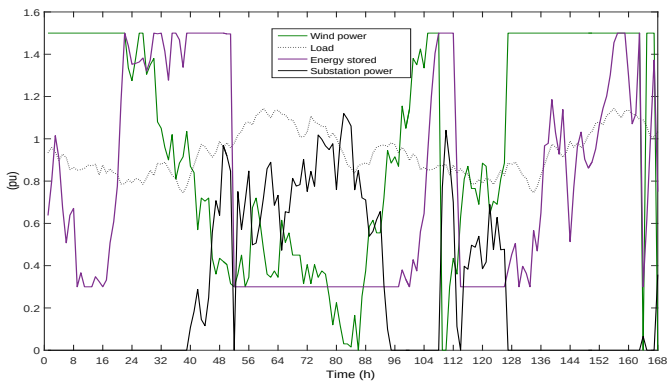

Figure 7. Energy stored in Case 9 in one scenario.

5. Conclusions

A new model for the joint allocation of wind power generation and generic ESS has been implemented in this paper. In order to optimize the operation of a distribution system, a model is proposed to select the best allocation of wind and ESS within a linear AC OPF representing the performance of the model. To demonstrate the capability of the proposed stochastic procedure, it has been applied to an IEEE 69-bus system, where load, price at the substation, and wind scenarios are also considered. It can be concluded that: (i) the proposed MILP is well suited for finding the proper locations of wind and ESS; (ii) total operating costs are reduced with the combination of these technologies; (iii) the benefit of integrating ESS in a distributed network with wind power units is demonstrated.

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Notations

Indexes

i,j,k	Bus indexes
r	Piecewise linearization (PWL) block index
t	Real-time period index on a 10-min basis
ω	Scenario index

Parameters

C^{loss}	Power losses penalization cost ($/MWh)
C^{p}	Production cost of the storage unit ($/MWh)
C^{s}	Storage cost of the storage unit ($/MWh)
$C^{\text{sub}}_{it\omega}$	Cost of real power from substation ($/MWh)
$C^{V_{\text{dev}}}$	Voltage deviation penalization cost ($/MWh)
$C^{\text{w\_curt}}$	Wind curtailment cost ($/MWh)
$\overline{I}^2_{ij}$	Maximum current flow through branch ij (A)
N^{st}	Number of storage units in the distribution network
N^{wind}	Number of wind units in the distribution network
$P^{\text{w\_fore}}_{it\omega}$	Wind power forecast at node i, period t and scenario ω (MW)
$Q^{\text{dem}}_{it\omega}$	Reactive power demand at node i, period t and scenario ω (MVaR)
R_{ij}	Resistance of branch ij (Ω)
R^{nom}	Nominal voltage of the distribution network (kV)
$\underline{s}^{\text{p}}_i, \overline{s}^{\text{p}}_i$	Minimum/maximum production of the storage unit at node i (MW)
$\underline{s}^{\text{s}}_i, \overline{s}^{\text{s}}_i$	Minimum/maximum storage of the unit at node i (MW)
V_{nom}	Nominal voltage of the distribution network (kV)
$\underline{x}_i, \overline{x}_i$	Minimum/maximum storage capacity at node i (MWh)
Δ	Time period (1 h) (h)
$\eta^{\text{p}}_i, \eta^{\text{s}}_i$	Efficiency production/storage rates of the storage units at node i

Variables

$\vec{I}_{ij}^{*}$	Conjugate value of the current flow through branch *ij* (A)
$\vec{I}_{ij}$	Phasor magnitude of the current flow through branch *ij* (A)
$I_{ijt\omega}^{2}$	Square of the current flow through branch *ij* (A^2)
$m_{ijrt\omega}$	Slope of the *r*-th block of the PWL
$P_{it\omega}^{\text{sub}}$	Real power of the substation (MW)
$P_{ijt\omega}^{+}$	Real power flow (downstream) (MW)
$P_{ijt\omega}^{-}$	Real power flow (upstream) (MW)
$P_{it\omega}^{\text{w\_curt}}$	Real power wind curtailment at bus *i* (MW)
$P_{it\omega}^{\text{wind}}$	Real power of wind turbine at bus *i* (MW)
$P_{ijt\omega}^{2}$	Square value of the real power flow (MW^2)
PF_{i}^{wind}	Power factor of the wind generation
$Q_{it\omega}^{\text{wind}}$	Reactive power of wind turbine at bus *i* (MVaR)
$Q_{it\omega}^{\text{sub}}$	Reactive power of the substation (MVaR)
$Q_{ijt\omega}^{+}$	Reactive power flow (downstream) (MVaR)
$Q_{ijt\omega}^{-}$	Reactive power flow (upstream) (MVaR)
$Q_{ijt\omega}^{2}$	Square value of the reactive power flow ($MVaR^2$)
$Q_{it\omega}^{\text{wind}}$	Reactive power of wind turbine at bus *i* (MVaR)
$s_{it\omega}^{\text{s}}$	Scheduled power production/storage reserve (MW)
$s_{it\omega}^{\text{p}}$	Scheduled power production/storage reserve (MW)
$\vec{V}_{i}$	Phasor magnitude of the voltage (kV)
$V_{it\omega}^{2}$	Square of the voltage magnitude of node *i* (kV^2)
$v_{ijt\omega}^{P^+}$	Binary variable related to real power (upstream)
$v_{ijt\omega}^{P^-}$	Binary variable related to real power (downstream)
$v_{ijt\omega}^{Q^+}$	Binary variable related to reactive power (upstream)
$v_{ijt\omega}^{Q^-}$	Binary variable related to reactive power (downstream)
$x_{it\omega}$	Storage level at node *i* (MWh)
α_{i}	Binary variable for wind power unit location
β_{i}	Binary variable for storage unit location
$\psi(\omega)$	Total cost of power losses and voltage deviation ($)
$\kappa(\omega)$	Total costs of wind and demand curtailments and ESS operation ($)
$\Delta P_{ijrt\omega}$	Value of the r-th block of real power (MW)
$\Delta Q_{ijt\omega}$	Value of the r-th block of reactive power (MVaR)
$\Delta S_{ijrt\omega}$	Value of the r-th block of apparent power (MVA)
θ_{ij}	Phasor of the angle (rad)

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Chapter 5

Impact of Electric Vehicles on the Expansion Planning of Distribution Systems considering Renewable Energy, Storage and Charging Stations

Impact of Electric Vehicles on the Expansion Planning of Distribution Systems considering Renewable Energy, Storage and Charging Stations

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***Abstract*—Energy storage systems (ESS) have adopted a new role with the increasing penetration of electric vehicles (EVs) and renewable energy sources (RES). EVs introduce new charging demands that change the traditional demand profiles and RES are characterized by their high variability. This paper presents a new multistage distribution expansion planning model where investments in distribution network assets, RES, ESS and EV charging stations (EVCS) are jointly considered. The charging demand necessary for EVs transportation is performed using a vehicle model based on travel patterns. The variability associated with RES along with the demand requires the incorporation of uncertainty, which is characterized through a set of scenarios. These scenarios are generated by the k-means++ clustering technique that allows keeping the correlation in the information of the uncertainty sources. The resulting stochastic program is driven by the minimization of the present value of the total expected cost including investment, maintenance, production, losses and non-supplied energy. The associated scenario-based deterministic equivalent is formulated as a mixed-integer linear program, which can be solved by commercial software. Numerical results are presented for an illustrative 54-node test system.**

***Index Terms*—Clustering technique, distribution system expansion planning (DSEP), ESS, EV charging demand, renewable energy.**

NOMENCLATURE

A. Indexes

a	Index for assets
b	Index for day/night time block
ch	Index for EVCS
i, j	Indexes for nodes
k	Index for alternatives
l	Index for feeder types
p	Index for distributed generation (DG) types
q	Index for quarters
t, τ	Index for time stages
tr	Index for transformers
ω	Index for scenarios

B. Sets

A	Set of assets, $A = \{L, TR, SS, P, CH\}$
B	Set of blocks (day and night)
CH	Set of EVCS types. $CH = \{NCH, ACH\}$ where NCH and ACH denote new and additional capacity for EVCS, respectively
K^l, K^{tr}, K^p K^{ST}, K^{ch}	Set of alternatives of feeders, transformers, DG, ESS and EVCS
L	Set of feeder types. $L = \{EFF, ERF, NRF, NAF\}$ where EFF, ERF, NRF, and NAF denote existing fixed feeders, existing replaceable feeders, new replacement feeders, and newly added feeders
P	Set of DG types. $P = \{W, \Theta\}$ where W and Θ denote wind power and photovoltaic generation (PV), respectively
Q	Set of quarters (4 seasonal quarters)
T	Set of time stages
TR	Set of transformer types. $TR = \{ET, NT\}$ where ET and NT denote existing transformer and new transformer, respectively
$\Omega^N, \Omega_i^l, \Omega_t^{LN}$ $\Omega^{SS}, \Omega^p,$ Ω^{ST}, Ω^{ch}	Set of system nodes, nodes connected to node i by a feeder of type l, load nodes, substation nodes, candidate nodes for DG, candidate nodes for ESS and candidate nodes for EVCS
Π	Set of scenarios
Υ^l	Set of branches with feeders of type l

C. Parameters

$C_k^{I,l}, C_i^{I,SS}, C_k^{I,NT}$ $C_k^{I,p}, C_k^{I,ST}, C_k^{I,ch}$	Investment cost of feeders, substations, new transformers, DG, ESS and EVCS
$C_k^{M,l}, C_k^{M,tr}, C_k^{M,}$ $C_k^{M,ST}, C_k^{M,ch}$	Maintenance cost of feeders, transformers, DG, ESS and EVCS
$C_{tqb\omega}^{SS}$	Cost of the energy purchased at the substation
$C_k^{E,p}$	Production cost of DG
$C_k^{ST,prod}$	Production cost of ESS
$C_k^{ST,store}$	Storage cost of ESS
C^U	Cost of the unserved energy
$D_{itqb\omega}$	Nodal demand
$dem_{tqb\omega}^{EV}$	Total EV charging demand needed in the whole system
$\bar{F}_{ijk}^l$	Upper limit for actual current flows through feeders
$\bar{G}_k^{tr}$	Upper limit for energy supplied by a transformer of type tr
$\bar{G}_k^p$	Maximum capacity of a generator of type p
$\hat{G}_{iktqb\omega}^p$	Maximum power availability of a generator of type p
$\underline{G}_k^{ST}$	Minimum capacity of ESS
$\bar{G}_k^{ST}$	Maximum capacity of ESS
$\bar{G}_k^{ch}$	Maximum capacity of an EVCS
I	Annual investment rate
IB_t	Investment limit at stage t
l_{ij}	Feeder length
n_{DG}, n_T	Number of candidate nodes for DG and number of time stages

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pf	System power factor
RR^a	Capital recovery rates for each asset
Z_k^l, Z_k^{tr}	Unitary impedance magnitude of feeders type l and impedance magnitude of transformers
$\pi_{qb\omega}$	Weight of scenario ω in day/night block b for quarter q
Δ_{qb}	Duration in hours of day/night block b for quarter q
$\eta_{lk}^{ST,prod}$	Production efficiency rate for ESS
$\eta_{lk}^{ST,store}$	Storage efficiency rate for ESS
ε	Penetration limit for generation
v^a	Lifetime of asset a [number of stages]

D. Variables

c_t^I	Investment cost at stage t
c_t^E	Energy production cost at stage t
c_t^M	Maintenance cost at stage t
c_t^R	Energy losses cost at stage t
c_t^U	Unserved energy cost at stage t
$d_{itqb\omega}^{ch}$	Charging demand in EVCS at node i
$d_{itqb\omega}^{U}$	Nodal unserved energy
$f_{ijktqb\omega}^{l}$	Current flow through alternative k of feeder type l installed in branch ij at stage t, day/night block b for quarter q and scenario ω, measured at node i. It is greater than 0 if node i is the supplier and 0 otherwise
$g_{iktqb\omega}^{p}$	Energy supplied by a generator of type p
$g_{iktqb\omega}^{tr}$	Energy supplied by a transformer of type tr
$g_{iktqb\omega}^{ST,prod}$	Power production of a ESS
$g_{iktqb\omega}^{ST,store}$	Power stored of a ESS
$x_{it}^{SS}, x_{ikt}^{NT}, x_{ijkt,}^{l}$ $x_{ikt}^{p}, x_{ikt}^{ST}, x_{ikt}^{ch}$	Binary investment variable for substations, new transformers, feeders, DG, ESS and EVCS
$u_{iktqb\omega}^{ST,prod}$, $u_{iktqb\omega}^{ST,store}$	Binary variables related to production and storage of ESS
$y_{it}^{SS} y_{ikt}^{NT}, y_{ijkt,}^{l}$ $y_{ikt}^{p}, y_{ikt}^{ST}, y_{ikt}^{ch}$	Binary utilization variable for substations, new transformers, feeders, DG, ESS and EVCS
$v_{itqb\omega}$	Nodal voltage

I. Introduction

A. Motivation

FUTURE decisions in DSEP models should consider the optimal location and sizing of EVCS, ESS and renewable DG. Their inappropriate location could have negative effects on the distribution system increasing power losses and degrading voltage profiles at some nodes [1]. Recently, EVs have aroused extensive attention due to the growing concerns in greenhouse gas emissions. More and more, EVs will be integrated in electrical power systems through charging facilities. This would generate a significant charging demand with uncertainties that along with the uncertainties arising from renewable energy may create an important challenge to new distribution systems. In order to deal with this problem, the estimation of the additional EV demand has to be done by using a vehicle decision algorithm considering EV travel data based on some assumptions on when EVs need to be charged. Moreover, the value of ESS relies on the existence of additional capacity to the grid, which represents an important issue to the increasing penetration of renewable energy and EV charging demand, while reducing generation costs.

Traditionally, multistage distribution planning models have been used to optimize generation investment meeting the growing demand in a centralized framework. In a more recent context, where renewable energy is increasing, uncertainty has to be considered in the model. Hence, one of the key aspects related to investment decisions is to represent the uncertainty and the correlation of the stochastic data information (load, wind speed, solar irradiation, cost of the energy at the substation and EV charging demand). A clustering technique, the k-means++ algorithm, is used to arrange data in groups according to their similarities, reducing the historical data into a large enough set of clusters and maintaining the correlation of the initial data. A detailed representation of the whole model is presented in the following sections.

This work stresses the importance of integrating ESS in distribution and generation system expansion planning given that medium-voltage EVCS should be appropriately located and sized in order to minimize the present value of the overall generation and distribution costs.

B. Literature Review

In the last few years, some models have been developed in distribution system planning within a centralized framework. Conventional planning models have solved the optimal expansion of distribution assets with the replacement and addition of feeders, the reinforcement of existing substations and the construction of new substations [2]. In [3], a review of the state-of-art of DSEP is presented. The increasing penetration of DG, run on renewable energy, requires its incorporation in distribution planning models to decide its location and timing [4]-[7]. Additionally, the uncertainty related to the unpredictability of the RES is commonly considered. In [4] the uncertainties in demand and DG are represented based on the theory of multiple scenarios running a genetic algorithm. In [5], the uncertainty related to load and electricity price is modeled through Monte Carlo simulation. In [6], a scenario-based stochastic programming framework is used to minimize the present value of the expected investment and operational cost in DSEP under correlated uncertainty based on duration curves. Similarly, in [7], demand response and ESS are also included in the distribution and generation expansion planning.

Other works have studied the operational planning of ESS. In [8], the concept of system states as opposed to load level duration curves (as in [6], [7]) is introduced, allowing for a better incorporation of chronological information. In [9], the optimal operation planning of batteries in distribution networks is performed by metaheuristic methods using probabilistic variation of the inputs with the point estimation method for optimal planning of batteries. In [10], a multistage expansion planning model for replacing and adding circuits is performed,

in which typical daily scenarios are assessed for the hourly economic dispatch of the ESS. Some works include the existence of EV loads in the joint distribution, generation and ESS expansion planning without including the installation cost in EVCS. In [11], a non-parametric chance-constrained optimization to invest in ESS units is proposed, in which the uncertainties of DGs and EVs, were considered using the probability density function. In [12], a multi-objective optimal planning of battery energy storage and DG units in an active distribution network is presented, in which the power profile of the EVs was modeled by fuzzy values.

Recently, more attention has been paid to the optimal planning of EVCS. In [13], the optimal planning of EVCS in distribution systems is developed with the minimization of total costs. In [14], a multi-objective mixed integer non-linear programming planning model is proposed for the new and replaced distribution network assets, EVCS and losses. In [15] a multi-objective planning model of a distribution network containing DG and EVCS is implemented. A scenario expansion planning for distribution systems is proposed in [16] considering the integration of EV, with dumb charging and coordinated charging modes.

In contrast to [10]-[12], our paper considers the investment decisions in EVCS. Additionally, different from [13]-[15], our paper jointly incorporates the expansion planning decision model of the network, DG (both wind and PV) and ESS investments. In [7], the goal is to maximize the net social benefit of the system being represented by the present value of the total payment of the consumers minus the present value of the total costs. In our paper, the objective is also different, as we are minimizing the total costs of expansion planning with the interaction of ESS and EV. Furthermore, in [7] the approach is different due to introduction of demand response related with the management of the active demand. Unlike [6] and [7], the scenarios are obtained using a clustering technique while also including the uncertainty associated with the cost of the energy purchased at the substation. This technique is better suited than the duration curves applied in [7]. Likewise, as said in [19], the k-means++ technique allows representing the operating conditions comparatively with greater accuracy.

C. Paper Contributions and Organization

TABLE I
COMPARISON OF THE INVESTMENT DECISIONS PLANNING MODELS

Approach	Network Investment	RES Investment	ESS Investment	EVCH Investment
[2]	✓	×	×	×
[4-6]	✓	✓	×	×
[7]	✓	✓	✓	×
[9]	×	×	✓	×
[10]	✓	×	×	×
[11]	×	×	✓	×
[12]	×	✓	✓	×
[13]	×	×	×	✓
[14]	✓	×	×	✓
[15]	✓	✓	×	✓
[16]	✓	×	×	×
Proposed approach	✓	✓	✓	✓

Table I summarizes the contents of the state-of-art in comparison with our work. Note that, as described in the literature review, some works already consider the existence of ESS, EV and RES without focusing on the corresponding investment decisions.

The main contributions of this paper are:

- The model includes the expansion planning of the distribution system including new and replacement feeders, new substations, additional transformers, RES, ESS, EVCS and additional capacity in the stations, simultaneously. The combination of the investment decisions of all these assets has not been presented yet.
- The prospective model stresses the relevance of integrating ESS in investment models under the increasing penetration of RES and the upcoming integration of EV under uncertainty. The main goal of this paper it is to show and analyze the interaction between ESS and EV.
- A scenario-based stochastic programming model is used to take into account the uncertainty of demand, the cost of the energy purchased at the substation, wind power, PV and EV charging demand.
- The associated deterministic equivalent is formulated as a mixed-integer linear programming model suitable for commercially available software.

The rest of the paper is organized as follows. The methodology to model EV charging demand and scenarios are presented in Section II. In Section III, the stochastic programming model for cost minimization is formulated. In Section IV, the case study and the results are reported. Finally, conclusions are drawn in Section V.

II. METHODOLOGY

In this section, we describe how to estimate the additional EV demand that needs to be considered in the optimal expansion planning of the whole system and the k-means++ clustering technique used to characterize the uncertain nature of the inputs and their correlation.

A. Modeling for EV Charging Demand

The increasing number of EVs connected for charging has a significant impact on several power system parameters, such as generation capacity, transformer loading level, line congestion level and load profile. Therefore, the expected increasing penetration of EV calls for the estimation of the additional demand.

We propose a method based on realistic vehicle statistics extracted from the 2009 (US) National Highway Travel Survey (NHTS) data [17] to calculate the total charging demand for all EVs. This survey includes data of each household, type of vehicle, trip distance, start and end time, month, day of the week, trip purpose and the location (city in the US) where these trips take place. A trip is the journey done by a vehicle when it goes from the driver's home to his/her workplace, or a commercial area, and vice versa. Due to the lack of data of EV travel patterns, we assume them to be the same as the traditional fossil-fueled ones.

To estimate the charging demand for EVs, a vehicle decision model has been implemented in MATLAB [18] as presented in Fig. 1. First, we exclude the trips with mileage greater than the maximum mileage driven using electricity. The proposed methodology comprises six steps that are described as follows:

1) For each vehicle *v*, a battery capacity is assigned randomly (24 kWh, 30 kWh, 36 kWh). We assume that all EVs are fully charged at the beginning of the first trip.

2) For each vehicle *v,* month *m* and day *d*, a trip *T* is assigned.

3) The model checks the state of charge (SOC) of the battery when the vehicle finishes trip *T*.

4) If the SOC does not reach the minimum (20% of the battery capacity), the algorithm looks for the next trip of the data set computing and updating the charging demand.

5) If the SOC reaches the minimum it is assumed that the vehicle charges its battery prior to that trip *T* in the interval of time (between trip *T*-1 and *T*) that vehicle *v* is stopped. Then, the SOC of the battery is checked again. In case the minimum is still reached the trip is excluded and the algorithm looks for the next trip.

6) After the last trip the algorithm iteratively runs along days, months and vehicles.

The charging time depends on three factors: battery capacity, SOC and power level of the charger. We consider a normal power supply of 3.3 kW at the EVCS. Hence, the total EV charging demand for all the vehicles is computed per hour, day, month and time stage (year) for the entire system as the final result of Fig. 1.

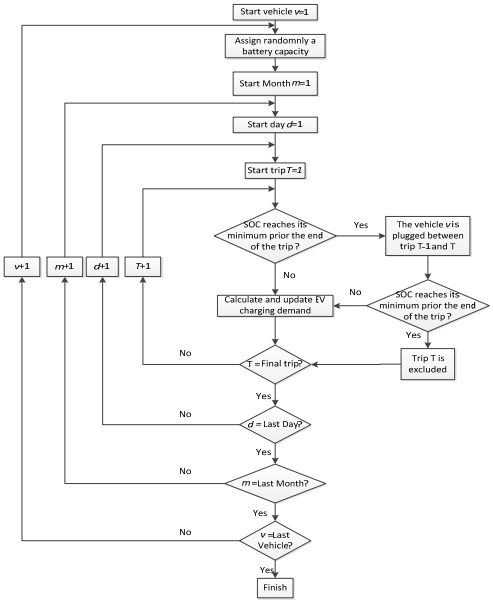

Fig 1. Flowchart of the vehicle decision model.

B. Uncertainty: K-means++ Method

The incorporation of renewable DG and EVCS in the multistage expansion planning of distribution systems yields new sources of uncertainty associated with the variability of RES and EV charging demand. Such uncertainty sources along with the conventional uncertainty associated with demand and the cost of energy purchased at the substation are considered. To that end, the variability of load demand, EV charging demand, wind speed, solar irradiation and cost of energy at the substation is characterized through a scenario-based stochastic programming framework. The set of scenarios is built on historical hourly data through the clustering technique shown in [19], allowing to keep the correlation among the initial uncertain data as in [20].

In this paper we use the k-means++ algorithm from Matlab [18] due to its simplicity and good performance. K-means clustering is based on computational geometry. The goal is to arrange the data into groups according to their similarities. A certain number of centers (centroids) are chosen in order to reduce the initial data based on the mathematics: minimizing the total squared distance between each point and its closest center. In this way, the parameters of the initial point are correlated to the values of its closest center.

With the purpose of minimizing the loss of information of the sequence between hours, the historical data is split into quarters (winter, spring, summer and autumn) as it is needed for representing the transition function of the ESS. The k-means ++ algorithm is applied 8 times, for each quarter (winter, spring, summer and autumn) and day/night block, so there are 4 quarters and 2 day/night blocks. Finally, the set of scenarios at each stage is represented by a matrix of 96 operating conditions (12 clusters per quarter and block × 4 quarters × 2 blocks) × 5 uncertain parameters. In this matrix, each operating condition includes 5 uncertain parameters: load, EV demand, wind speed, solar irradiation and cost of the energy purchased at the substation.

The k-means methodology uses an iterative algorithm. In this paper, specifically, we have used k-means++ implemented in Matlab R2016b. In data mining, k-means++ is an algorithm to choose the initial values (or "seeds") of the k-means clustering algorithm. This algorithm improves the initialization of the centroids before starting the standard k-means, guaranteeing a faster and better solution [21].

The algorithm works as follows:

Step 1) Select the number of required clusters *K*, according to the needs of the problem. This number should encompass a good representation of the operating conditions of the system.

Step 2) Take one centroid, chosen uniformly at random from initial data set (x). D(x) denotes the shortest distance from a data point to the closest center, which has been already chosen.

Step 3) Take a new centroid, c_i, choosing x with probability $\frac{D(x)^2}{\sum_x D(x)^2}$.

Step 4) Repeat step 3 until there are *K* centers altogether.

Step 5) Compute the distances between each data point and each cluster centroid based on the use of Euclidean distances.

Step 6) Assign each point of the data to the closest centroid based on the use of Euclidean distances.

Step 7) Recalculate the cluster centroids, c_i, to be the center of mass of all points in C_i equal to:

$$\frac{1}{|C_i|}\sum_{x \in Ci} x$$

Steps 5–7 are performed iteratively until the cluster compositions do not vary between two consecutive iterations. The cluster centroids (the matrix of 96 values x 5 parameters) are the output of this algorithm as well as the number of observations assigned to each cluster. The observations are

hourly historical data. Each cluster centroid is represented by the values of the cost of the energy purchased at the substation, wind speed, solar irradiation, load and EV charging demand, which show a system operating condition. For each day/night block b and quarter q, the probability of each scenario is determined by the number of observations within each cluster divided by the total number of observations of the corresponding block b and quarter q.

III. Problem Formulation

In the multistage expansion planning model, a scenario-based stochastic programming is used to minimize the present value of the expected total cost of the distribution network from a centralized framework viewpoint. The proposed model is built on an associated scenario-based deterministic equivalent formulated as a MILP in which i) the planning horizon is divided into T stages of known duration, ii) radial operation is explicitly imposed, iii) an approximate network model is used, iv) several investment alternatives exist for each asset, and v) a perpetual planning horizon is considered for the operating costs.

A. Objective Function

The model minimizes the present value of the total expected cost:

$$min = \left\{ \sum_t \frac{(1+I)^{-t}}{I} c_t^I + \left[\sum_t (1+I)^{-t} \left(c_t^M + c_t^E + c_t^R + c_t^U\right) + \frac{(1+I)^{-n_T}}{I} \left(c_{n_T}^M + c_{n_T}^E + c_{n_T}^R + c_{n_T}^U\right) \right] \right\} \tag{1}$$

where:

$$\begin{aligned} c_t^I = & \sum_{l\in\{NRF,NAF\}} RR^l \sum_{k\in K^l} \sum_{(i,j)\in\Upsilon^l} C_k^{I,l} \ell_{ij} x_{ijkt}^l + \\ & RR^{SS} \sum_{i\in\Omega^{SS}} C_i^{I,SS} x_{it}^{SS} + \\ & RR^{NT} \sum_{k\in K^{NT}} \sum_{i\in\Omega^{SS}} C_k^{I,NT} x_{ikt}^{NT} + \\ & \sum_{p\in P} RR^p \sum_{k\in K^p} \sum_{i\in\Omega^p} C_k^{I,p} pf \bar{G}_k^p x_{ikt}^p + \\ & RR^{ST} \sum_{k\in K^{ST}} \sum_{i\in\Omega^{ST}} C_k^{I,ST} pf \bar{G}_k^{ST} x_{ikt}^{ST} + \\ & \sum_{ch\in CH} RR^{ch} \sum_{k\in K^{ch}} \sum_{i\in\Omega^{ch}} C_k^{I,ch} pf \bar{G}_k^{ch} x_{ikt}^{ch}, \ \forall t \in T \end{aligned} \tag{2}$$

$$\begin{aligned} c_t^M = & \sum_{l\in L} \sum_{k\in K^l} \sum_{(i,j)\in\Upsilon^l} C_k^{M,l} \left(y_{ijkt}^l + y_{jikt}^l\right) + \\ & \sum_{tr\in TR} \sum_{k\in K^{tr}} \sum_{i\in\Omega^{SS}} C_k^{M,tr} y_{ikt}^{tr} + \sum_{p\in P} \sum_{k\in K^p} \sum_{i\in\Omega^p} C_k^{M,p} y_{ikt}^p + \\ & \sum_{k\in K^{ST}} \sum_{i\in\Omega^{ST}} C_k^{M,ST} y_{ikt}^{ST} + \sum_{ch\in CH} \sum_{k\in K^{ch}} \sum_{i\in\Omega^{ch}} C_k^{M,ch} y_{ikt}^{ch}; \\ & \forall t \in T \end{aligned} \tag{3}$$

$$\begin{aligned} c_t^E = & \\ = & \sum_{q\in Q} \sum_{b\in B} \sum_{\omega\in\Pi} \pi_{qb\omega} \Delta_{qb}\, pf \Bigg(\sum_{tr\in TR} \sum_{k\in K^{tr}} \sum_{i\in\Omega^{SS}} C_{tqb\omega}^{SS} g_{iktqb\omega}^{tr} \\ & + \sum_{p\in P} \sum_{k\in K^p} \sum_{i\in\Omega^p} C_k^{E,p} g_{iktqb\omega}^p \\ & + \sum_{k\in K^{ST}} \sum_{i\in\Omega^{ST}} C_k^{ST,prod} g_{iktqb\omega}^{ST,prod} + \\ & \sum_{k\in K^{ST}} \sum_{i\in\Omega^{ST}} C_k^{ST,store} g_{iktqb\omega}^{ST,store} \Bigg); \ \forall t \in T \end{aligned} \tag{4}$$

$$\begin{aligned} c_t^R = & \sum_{q\in Q} \sum_{b\in B} \sum_{\omega\in\Pi} \pi_{qb\omega} \Delta_{qb} C_{tqb\omega}^{SS} pf \\ & \Bigg(\sum_{tr\in TR} \sum_{k\in K^{tr}} \sum_{i\in\Omega^{SS}} Z_k^{tr} \left(g_{iktqb\omega}^{tr}\right)^2 + \\ & \sum_{l\in L} \sum_{k\in K^l} \sum_{(i,j)\in\Upsilon^l} Z_k^l \ell_{ij} \left(f_{ijktqb\omega}^l + f_{jiktqb\omega}^l\right)^2 \Bigg); \ \forall t \in T \end{aligned} \tag{5}$$

$$c_t^U = \sum_{q\in Q} \sum_{b\in B} \sum_{\omega\in\Pi} \pi_{qb\omega} \Delta_{qb} C^U pf \sum_{i\in\Omega_t^{LN}} d_{itqb\omega}^U; \ \forall t \in T \tag{6}$$

The objective function (1) contains three terms. The first one corresponds to the present worth value of the investment cost under the assumption of a perpetual or infinite planning horizon [22]. That is, the investment cost is amortized annually throughout the lifetime of the assets, considering that after their lifetime has expired there is a reinvestment in an identical equipment. The second term is the present value of the operating costs throughout the time stages. Lastly, the third term shows the present value of the operating costs incurred after the last time stage assuming a perpetual planning.

The total cost (1) comprises five different costs, namely investment cost (2), maintenance cost (3), production cost (4), cost of energy losses (5), and unserved energy costs (6).The capital recovery rates for investing in feeders, new transformers, substations, generators, ESS and EVCS are calculated in a generic form as $RR^a = I(1+I)^{v^a}/((1+I)^{v^a} - 1)$, which are dependent on the lifetime of each asset. It is noticeable that two binary variables are associated with each feeder in order to model its utilization in the directions, y_{ijkt}^l and y_{jikt}^l. The same occurs with the current flow through the feeder. The energy losses are formulated as quadratic terms and are linearized approximating them by a set of tangent lines. This can be seen in section III.E in [6].

B. Constraints

Firstly, the constraints related with the technical operation of the system such as Kirchhoff Laws and operational limits are formulated. In (7) the nodal current flow balance equation is stated. In (8) the Kirchhoff Voltage Law for all feeders is represented. Note this constraint includes nonlinearities which are recast as linear expressions as provided in section III.E in [6]. Constraint (9) sets the bounds on the magnitudes of nodal voltages. In (10)-(13), the upper and lower limits on the current flow and generation power are represented. In (14), the level of

penetration of DG is limited as a fraction ε of the load and charging demand.

$$\sum_{l\in L}\sum_{k\in K^l}\sum_{j\in\Omega_i^l}\left(f_{ijktqb\omega}^l - f_{jiktqb\omega}^l\right) = \sum_{tr\in TR}\sum_{k\in K^{tr}} g_{iktqb\omega}^{tr} + \sum_{p\in P}\sum_{k\in K^p} g_{iktqb\omega}^{p} + \sum_{k\in K^{st}} g_{iktqb\omega}^{ST,prod} - \sum_{k\in K^{st}} g_{iktqb\omega}^{ST,store} - D_{itqb\omega} - d_{itqb\omega}^{U} - d_{itqb\omega}^{CH};\ \forall i\in\Omega^N, \forall t\in T, \forall q\in Q, \forall b\in B, \forall\omega\in\Pi \tag{7}$$

$$y_{ijkt}^l\left[Z_{ijk}^l \ell_{ij} f_{ijktqb\omega}^l - \left(v_{itqb\omega} - v_{jtqb\omega}\right)\right] = 0;\ \forall l\in L, \forall i\in\Omega_j^l, \forall j\in\Omega^N, \forall k\in K^l, \forall t\in T, \forall q\in Q, \forall b\in B, \forall\omega\in\Pi \tag{8}$$

$$\underline{V} \le v_{itqb\omega} \le \overline{V};\ \forall i\in\Omega^N, \forall t\in T, \forall q\in Q, \forall b\in B, \forall\omega\in\Pi \tag{9}$$

$$0 \le f_{ijktqb\omega}^l \le y_{ijkt}^l \bar{F}_{ijk}^l;\ \forall l\in L, \forall i\in\Omega_j^l, \forall j\in\Omega^N, \forall k\in K^l, \forall t\in T, \forall q\in Q, \forall b\in B, \forall\omega\in\Pi \tag{10}$$

$$0 \le g_{iktqb\omega}^{tr} \le y_{ikt}^{tr}\bar{G}_k^{tr};\ \forall tr\in TR, \forall i\in\Omega^{SS}, \forall k\in K^{NT}, \forall t\in T, \forall q\in Q, \forall b\in B, \forall\omega\in\Pi \tag{11}$$

$$0 \le g_{iktqb\omega}^{p} \le y_{ikt}^{p}\,\hat{G}_{iktqb\omega}^{p};\ \forall p\in P, \forall i\in\Omega^p, \forall k\in K^p, \forall t\in T, \forall q\in Q, \forall b\in B, \forall\omega\in\Pi \tag{12}$$

$$0 \le d_{itqb\omega}^{U} \le d_{itqb\omega} + d_{itqb\omega}^{CH};\ i\in\Omega^N, \forall t\in T, \forall q\in Q, \forall b\in B, \forall\omega\in\Pi \tag{13}$$

$$\sum_{p\in P}\sum_{k\in K^p}\sum_{i\in\Omega^p} g_{iktqb\omega}^{p} + \sum_{k\in K^{ST}}\sum_{i\in\Omega^{ST}}\left(g_{iktqb\omega}^{ST,prod} - g_{iktqb\omega}^{ST,store}\right) \le \varepsilon\left(\sum_{i\in\Omega_t^{LN}} D_{itqb\omega} + d_{itqb\omega}^{CH}\right);\ \forall t\in T, \forall b\in B, \forall q\in Q, \forall\omega\in\Pi \tag{14}$$

The power supplied or stored by an ESS unit is bounded between the lower and upper capacity values, (15)-(16). When the ESS unit is used, to avoid simultaneous production and storage, two binary variables are defined in (17).

$$\underline{G}_k^{ST}\, u_{iktqb\omega}^{ST,prod} \le g_{iktqb\omega}^{ST,prod} \le \bar{G}_k^{ST}\, u_{iktqb\omega}^{ST,prod};\ \forall i\in\Omega^{ST}, \forall k\in K^{ST}, \forall t\in T, \forall q\in Q, \forall b\in B \forall\omega\in\Pi \tag{15}$$

$$\underline{G}_k^{ST}\, u_{iktqb\omega}^{ST,store} \le g_{iktqb\omega}^{ST,store} \le \bar{G}_k^{ST}\, u_{iktqb\omega}^{ST,store};\ \forall i\in\Omega^{ST}, \forall k\in K^{ST}, \forall t\in T, \forall q\in Q, \forall b\in B, , \forall q\in Q, \forall\omega\in\Pi \tag{16}$$

$$u_{iktqb\omega}^{ST,prod} + u_{iktqb\omega}^{ST,store} \le y_{ikt}^{ST};\ \forall i\in\Omega^{ST}, \forall k\in K^{ST}, \forall t\in T, \forall q\in Q, \forall b\in B, \forall q\in Q, \forall\omega\in\Pi \tag{17}$$

The utilization and investment constraints follow, in which a maximum of one reinforcement, replacement or addition is allowed for each system asset and location along the planning horizon, (18)-(23). In (24)-(25), new transformers can be added at substations as well as additional capacity in the EVCS, only if they have been built in any previous stage.

$$\sum_{t\in T}\sum_{k\in K^l} x_{ijkt}^l \le 1;\ \forall l\in\{NRF, NAF\}, \forall(i,j)\in\Upsilon^l \tag{18}$$

$$\sum_{t\in T} x_{it}^{SS} \le 1; \forall i\in\Omega^{SS} \tag{19}$$

$$\sum_{t\in T}\sum_{k\in K^{NT}} x_{ikt}^{NT} \le 1; \forall i\in\Omega^{SS} \tag{20}$$

$$\sum_{t\in T}\sum_{k\in K^p} x_{ikt}^{p} \le 1\,; \forall p\in P, \forall i\in\Omega^p \tag{21}$$

$$\sum_{t\in T}\sum_{k\in K^{ST}} x_{ikt}^{ST} \le 1;\ \forall i\in\Omega^{ST} \tag{22}$$

$$\sum_{t\in T}\sum_{k\in K^{ch}} x_{ikt}^{ch} \le 1;\ \forall ch\in CH, \forall i\in\Omega^{ch} \tag{23}$$

$$x_{ikt}^{NT} \le \sum_{\tau=1}^{t} x_{i\tau}^{SS};\ \forall i\in\Omega^{SS}, \forall k\in K^{NT}; \forall t\in T \tag{24}$$

$$x_{ikt}^{ACH} \le \sum_{\tau=1}^{t} x_{ik\tau}^{NCH}\,;\ \forall i\in\Omega^{ACH}, \forall k\in K^{ACH}; \forall t\in T \tag{25}$$

As seen in [6] and [7], we consider radial operation and meshed topologies. Equations (26)-(28) model the utilization of existing and new feeders indicating the direction of the current flows. Equation (28) model the utilization of the existing replaceable feeders while explicitly characterizing the direction of the current flows. These feeders can undergo replacement so that their utilization is subject to the installation of new replacement feeders, x_{ijkt}^{NRF}. Therefore, if an existing replaceable feeder is replaced by a new replacement feeder, i.e., $x_{ijkt}^{NRF} = 1$; the utilization of such existing replaceable feeder is disable with constraint (28).

The utilization of new transformers, installed generators, ESS, EV and EVCS are defined in (26)-(32).

$$y_{ijkt}^{EFF} + y_{jikt}^{EFF} \le 1; \forall(i,j)\in\Upsilon^{EFF}, \forall k\in K^{EFF}, \forall t\in T \tag{26}$$

$$y_{ijkt}^l + y_{jikt}^l \le \sum_{\tau=1}^{t} x_{ij k\tau}^l\,;\ \forall l\in\{NRF, NAF\}, \forall(i,j)\in\Upsilon^l, \forall k\in K^l, \forall t\in T \tag{27}$$

$$y_{ijkt}^{ERF} + y_{jikt}^{ERF} \le 1 - \sum_{\tau=1}^{t}\sum_{k\in K^{NRF}} x_{ij k\tau}^{NRF}\,;\ \forall(i,j)\in\Upsilon^{ERF}, \forall k\in K^{ERF}, \forall t\in T \tag{28}$$

$$y_{ikt}^{NT} \le \sum_{\tau=1}^{t} x_{ik\tau}^{NT}\,;\ \forall i\in\Omega^{SS}, \forall k\in K^{NT}, \forall t\in T \tag{29}$$

$$y_{ikt}^{p} \le \sum_{\tau=1}^{t} x_{ik\tau}^{p}\ ; \forall p\in P, \forall i\in\Omega^p, \forall k\in K^p, \forall t\in T \tag{30}$$

$$y_{ikt}^{ST} \le \sum_{\tau=1}^{t} x_{ik\tau}^{ST}\,;\ \forall i\in\Omega^{ST}, \forall k\in K^{ST}, \forall t\in T \tag{31}$$

$$y_{ikt}^{ch} \le \sum_{\tau=1}^{t} x_{ikt}^{ch}; \forall ch\in CH, \forall i\in\Omega^{ch}, \forall k\in K^{ch}, \forall t\in T \tag{32}$$

In (33), the total investment cost at each stage is limited by a maximum budget.

$$\sum_{l\in\{NRF,NAF\}}\sum_{k\in K^l}\sum_{(ij)\in\Upsilon^l} C_k^{l,l}\ell_{ij}x_{ijkt}^l + \sum_{i\in\Omega^{SS}} C_i^{l,SS}x_{it}^{SS} + \sum_{k\in K^{NT}}\sum_{i\in\Omega^{SS}} C_k^{l,NT}x_{ikt}^{NT} + \sum_{p\in P}\sum_{i\in\Omega^p} C_k^{l,p}pf\bar{G}_k^p x_{ikt}^p + \sum_{p\in P}\sum_{i\in\Omega^{ST}} C_k^{l,ST}pf\bar{G}_k^{ST}x_{ikt}^{ST} + \sum_{ch\in CH}\sum_{i\in\Omega^{CH}} C_k^{l,ch}pf\bar{G}_k^{ch}x_{ikt}^{ch} \le IB_t;\ \forall t\in T \tag{33}$$

In addition, in order to have a radial operation, equation (34) sets load nodes to have one input flow. In (35) the rest of the nodes are limited by a maximum of one input flow. Constraints (36)-(43) avoid isolated generators by modeling a fictitious system with fictitious demands as done in [6].

$$\sum_{l\in L}\sum_{i\in\Omega_j^l}\sum_{k\in K^l} y_{ijkt}^l = 1;\forall\, j\in\Omega_t^{LN},\forall t\in T \tag{34}$$

$$\sum_{l\in L}\sum_{i\in\Omega_j^l}\sum_{k\in K^l} y_{ijkt}^l \le 1;\forall\, j\notin\Omega_t^{LN},\forall t\in T \tag{35}$$

$$\sum_{l\in L}\sum_{k\in K^l}\sum_{j\in\Omega_i^l}\left(\tilde{f}_{ijkt}^l - \tilde{f}_{jikt}^l\right) = \tilde{g}_{it}^{SS} - \widetilde{D}_{it};\ \forall i\in\Omega^N,\forall t\in T \tag{36}$$

$$0 \le \tilde{f}_{ijkt}^{EFF} \le n_{DG};\ \forall\, i\in\Omega_j^{EFF},\forall j\in\Omega^N,\forall k\in K^{EFF},\forall t\in T \tag{37}$$

$$0 \le \tilde{f}_{ijkt}^{ERF} \le \left(1-\sum_{\tau=1}^{t}\sum_{\kappa\in K^{NRF}} x_{ij\kappa\tau}^{NRF}\right)n_{DG};\quad \forall(i,j)\in\Upsilon^{EFF},\forall k\in K^{ERF},\forall t\in T \tag{38}$$

$$0 \le \tilde{f}_{jikt}^{ERF} \le \left(1-\sum_{\tau=1}^{t}\sum_{\kappa\in K^{NRF}} x_{ij\kappa\tau}^{NRF}\right)n_{DG};\quad \forall(i,j)\in\Upsilon^{EFF},\forall k\in K^{ERF},\forall t\in T \tag{39}$$

$$0 \le \tilde{f}_{ijkt}^{l} \le \left(\sum_{\tau=1}^{t} x_{ijk\tau}^{l}\right)n_{DG};\quad \forall l\in\{NRF,NAF\},\forall(i,j)\in\Upsilon^l,\forall k\in K^l,\forall t\in T \tag{40}$$

$$0 \le \tilde{f}_{jikt}^{l} \le \left(\sum_{\tau=1}^{t} x_{ijk\tau}^{l}\right)n_{DG};\quad \forall l\in\{NRF,NAF\},\forall(i,j)\in\Upsilon^l,\forall k\in K^l,\forall t\in T \tag{41}$$

$$0 \le \tilde{g}_{it}^{SS} \le n_{DG};\ \forall i\in\Omega^{SS},\forall t\in T \tag{42}$$

where $\widetilde{D}_{it}$ is defined as follows:

$$\widetilde{D}_{it} = \begin{cases}1; & \forall i\in\Omega_t^{LN},\forall t\in T\\ 0; & \forall i\notin\Omega_t^{LN},\forall t\in T\end{cases} \tag{43}$$

In the case of considering that future networks had bidirectional flows and meshed operation were allowed, equations (34)-(35) should be deleted. However, when considering bidirectional flows and radial operation, equations (34)-(35) of the proposed paper should be replaced with equations (13)-(17) from [23]. These five equations should be adapted to the proposed multistage expansion planning model. Equations (34)-(35) impose the radiality condition per node, while equations (13)-(17) from [23] impose a general radiality condition for the whole network, where upstream flows are allowed.

ESS are good alternatives to integrate large amounts of intermittent renewable energy and improve network reliability because they are more efficient economically and avoid network oversizing. In medium- and long-term planning models, data has to be arranged in scenarios where chronological information is missing, the same as the transition function between hours. Similar to [7], we propose a representation of the transition function (44) to be achieved at the *b* level (day/night) in each quarter *q*, not being possible to exchange power between quarters.

$$\sum_b\left[\Delta_{qb}\left(\eta_i^{ST,store}\, g_{iktqb\omega}^{ST,store} - \left(\frac{1}{\eta_i^{ST,prod}}\right)g_{iktqb\omega}^{ST,prod}\right)\right] = 0;\ \forall i\in\Omega^{ST},\forall k\in K^{ST},\forall t\in T,\forall q\in Q,\forall\omega\in\Pi \tag{44}$$

In this context, for each quarter *q,* the energy can be exchanged (in some scenarios, the ESS produces or stores energy) between operating conditions of the same block *b* (day or night) and between day and night blocks. This can be seen in Fig. 2, in which there are 12 operating conditions in each block and the sum of the energy produced and stored by the ESS is equal to 0. Thus, in some operating conditions the demand increases and in other decreases. Note that each operating condition has a different duration with its corresponding scenario probability.

As mentioned in Subsection II.A, the additional demand needed for EVs in the distribution network, $dem_{tb\omega}^{CH}$, is calculated previously. Equation (45) satisfies the EVCS capacity limits of the charging demand required at the location nodes. Finally, in (46), the sum of the charging demands at all nodes where the EVCS is installed should satisfy the total EV demand needed for the whole system.

$$0 \le d_{itqb\omega}^{ch} \le \bar{G}_k^{ch}\, y_{ikt}^{ch};\quad \forall ch\in CH,\forall i\in\Omega^{ch},\forall k\in K^{ch},\forall t\in T,\forall b\in B,\ \forall q\in Q,\forall\omega\in\Pi \tag{45}$$

$$\sum_{ch\in CH}\sum_{i\in\Omega^{CH}} d_{itqb\omega}^{ch} = dem_{tqb\omega}^{EV};\forall t\in T,\forall b\in B,\ \forall q\in Q,\forall\omega\in\Pi \tag{46}$$

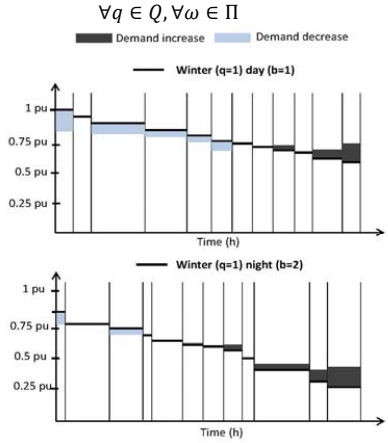

Fig 2. ESS effect on a particular load duration curve.

All the cases have been solved using MATLAB R2012a [18] and CPLEX 12.6 under GAMS 24.7 [25] on a SIE LADON with two Intel Xeon E5-2698 v3 processors clocking at 2.30 GHz and 256 GB of RAM. The stopping criterion is based on an optimality gap of 1%. The computation time for each case study is 455 s, 968 s and 12840 s, respectively.

A. Results without ESS and EV Charging Demand

In Fig. 4 the DSEP is shown with the corresponding replaced and added branches (including the time stage at which this takes place), RES location and new substations and transformers. Alternative 1 is selected by the model for renewable generation and branches. For the sake of simplicity, this has not been illustrated. This is common among all the cases. It is noticeable that all the candidate branches subject to replacement are replaced at stage 1. In addition, the alternative selected for the new substations is also represented in Fig. 4. We can observe that transformer 1 (10 MVA of capacity) and 2 (15 MVA of capacity) are required for new substations at nodes 53 and 54, respectively.

Table II depicts the stage at which the investment decisions and the node where wind generation, PV generation, new substations are built and the substations are expanded with new transformers. Note that the new substations are required at stages 1 and 2.

It is noticeable the high investment in renewables, in order to reduce the costs related to production and energy losses, as we allow a 40% penetration of DG and ESS. In Table III, the numerical disaggregated costs are presented, where the highest investment cost is at stage 4 corresponding to the construction of 3 wind units and 3 PV units as seen in Table II.

TABLE II
INVESTMENT DECISIONS LOCATION IN THE 15-YEAR EXPANSION PLANNING WITHOUT ESS AND EVCS

Investment	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
PV			12,30,35	8,20,37	2,22
Wind	3,10,16	24	44	38,42,47	
Transformers	54	53			

TABLE III
INVESTMENT AND OPERATIONAL COSTS IN THE 15-YEAR EXPANSION PLANNING WITHOUT ESS AND EVCS (10^6\$)

Costs	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5	Total
Investment	17.6	6.1	12.7	18.2	4.1	58.8
Maintenance	1.7	2.0	3.0	4.3	45.6	56.6
Production	38.1	46.4	55.5	60.4	737.1	937.4
Energy losses	1.7	2.1	2.6	3.0	40.8	50.2
Unserved energy	0	0	0	0	0	0
Total	59.0	56.7	73.9	85.9	827.6	1103.0

B. Results with EV Charging Demand

The topology in this situation, including also the EVCS, is shown in Figure 5. We can see that it has also changed slightly. Branch 1-9 (from node 1 to node 9) is replaced at stage 3. The other replacement candidate branches, as in case A, are replaced at stage 1.

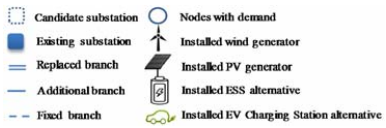

Fig 3. Legend of the on-line diagram of the network.

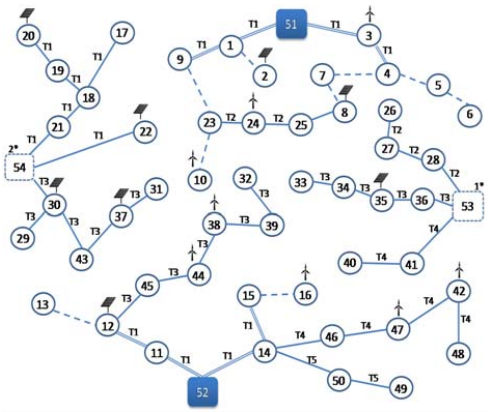

Fig 4. DSEP with network and RES assets.

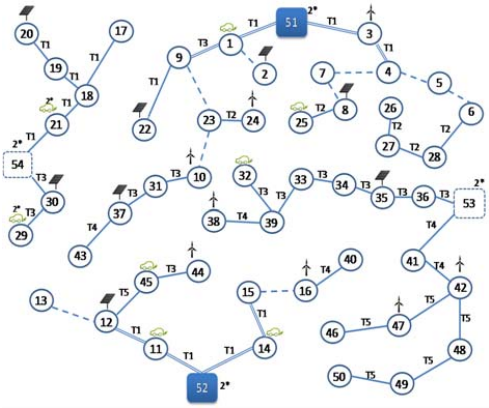

Fig 5. DSEP with network, renewable and EVCS assets.

In Tables IV both the location nodes and the stage of the investment decisions with EVCS are represented. In this case, the substation at node 53 delays its investment to stage 3. In addition to the increase in the total demand in the system, additional transformers are needed for the existing substations at nodes 51 and 52 (alternative 2 in both cases). Alternative 1 (1 MVA of capacity) is used for all EVCS, except for the one used at node 32. The EVCS located at nodes 21 and 29, constructed at stage 3, are expanded at stage 4 with alternative 2 (0.75 MVA of capacity).

Including the additional EVs demand in the model, we can see in Table V that every cost is higher than in case A, as expected. Furthermore, PV investment is slightly accelerated and more transformers are needed in comparison to case A resulting a high investment cost at stage 3.

TABLE IV
INVESTMENT DECISIONS LOCATION IN THE 15-YEAR EXPANSION PLANNING WITH EVCS

Investment	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
PV			8,12,30,35	20,22,37	2
Wind	3,10,16	24	44	38,42	47
Transformers	54		53	51	52
EVCS	21		29,32,45	21,25,29	1,11,14

TABLE V
INVESTMENT AND OPERATIONAL COSTS IN THE 15-YEAR EXPANSION PLANNING WITH EVCS (10^6\$)

Costs	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5	Total
Investment	18.2	4.7	18.1	16.9	7.9	65.8
Maintenance	1.7	1.9	3.4	4.5	50.0	61.4
Production	38.6	47.5	58.5	65.9	834.7	1045.2
Energy losses	1.8	2.9	3.4	3.6	47.1	58.8
Unserved energy	0	0	0	0	0	0
Total	60.2	57.1	83.4	90.9	939.6	1231.2

C. *Results with ESS and EV Charging Demand*

In this situation we add the possibility to invest in ESS units. The network configuration and new location of the assets is illustrated in Fig 6.

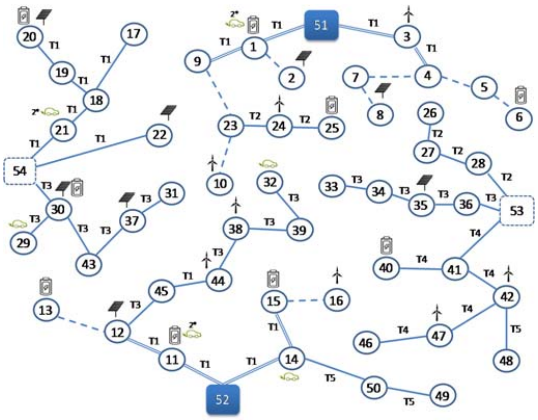

Fig. 6. DSEP with network, renewable, ESS and EVCS assets.

In Table VI, the locations and stages are presented. The renewable investment decision is similar to case B. Note that more ESS units are required at stage 5. The first alternative of the ESS is chosen for all the nodes in which there is a decision to invest in this technology. Moreover, no additional transformer is required in this case. The EVCS investment decision has changed in some stages compared to the previous case. Now, all the EVCS provided by the model are built with alternative 1 (3 MVA of capacity). However, at stage 5, the expansion in the EVCS located at nodes 11 and 21 takes place using alternative 2 only (0.75 MVA of capacity), being the same alternative provided by the model as in case B.

The costs are presented in Table VII. The energy purchased and energy losses costs are reduced due to existence of ESS. The overall cost is reduced by 3.8% considering the possibility to invest in storage technologies in comparison to case B. The existence of EV charging demand in the system stresses the importance of investing in this storage units.

The interaction of ESS with EV accelerates the investment in wind and the construction of a new substation. On the other hand, the investment in ESS avoids and defers the investment in new transformers in the existing substations. The effect of the ESS with EV is that the production and energy loss costs decrease, enhancing the total cost for the planner. The main conclusion is that integrating EVs in the distribution system makes the investment in ESS more profitable.

TABLE VI
INVESTMENT DECISIONS LOCATION IN THE 15-YEAR EXPANSION PLANNING WITH ESS AND EVCS

Investment	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
PV			12,20,30,35	2,8,37	22
Wind	3,10,16	24	38,44	42	47
Storage		1	30		6,11,13,15 20,25,40
Transformers	54	53			
EVCS	11		21,29,32	14	1,11,21

TABLE VII
INVESTMENT AND OPERATIONAL COSTS IN THE 15-YEAR EXPANSION PLANNING WITH ESS AND EVCS (10^6\$)

Costs	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5	Total
Investment	18.2	11.6	22.5	11.3	16.3	79.9
Maintenance	1.7	2.6	4.3	4.7	60.5	73.8
Production	38.6	45.9	55	63.6	780.3	983.4
Energy losses	1.7	2.2	2.6	3.0	39.7	49.2
Unserved energy	0	0	0	0	0	0
Total	60.2	62.3	84.4	82.6	896.8	1186.3

A sensitivity analysis has been performed with different values of the charging rate of the ESS, as shown in Fig. 7 and different penetration levels of DG with two different situations of the number of candidate buses for the placement of the assets investment, as seen in Fig. 8. Note that a less restrictive charging rate decreases the total investment and operational cost. Besides, the total cost of investment and operational costs decreases as the level of penetration in DG and the number of candidate buses for assets' placement increases.

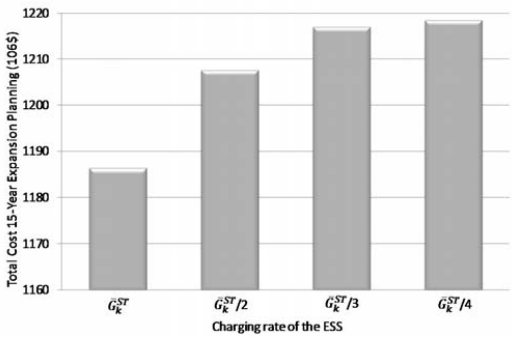

Fig. 7. Total cost of investment and operational costs in the 15-year expansion planning with ESS and EVCS vs. charging rate of the ESS.

Finally, in order to demonstrate and justify the effectiveness of using 96 operating conditions we have simulated other cases with different number of operating conditions for case study C, as seen in Table VIII.

Table VIII shows that the absolute value of the difference of the total cost with 24, 48, 192, 288, 384 and 480 scenarios minus the total cost of with 96 scenarios (base-case) decreases when selecting more scenarios.

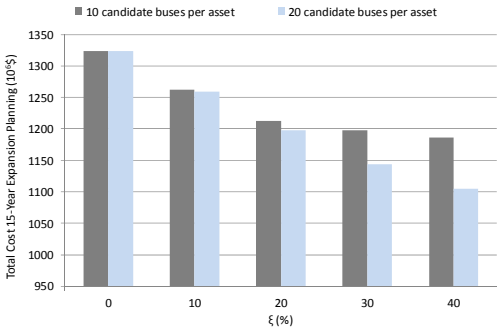

Fig. 8. Total cost of investment and operational costs in the 15-year expansion planning with ESS and EVCS vs. penetration level of DG and ESS.

TABLE VIII
TOTAL COSTS IN THE 15-YEAR EXPANSION PLANNING WITH ESS AND EV AS A FUNCTION OF THE NUMBER OF OPERATING CONDITIONS

Operating conditions	Total cost	Absolute value of the difference in (%)	CPU time (s)
24	1106.7	6.71 %	1521
48	1151.3	2.95 %	4333
96	1186.3	--	7908
192	1193.4	0.60 %	45070
288	1181.9	0.37 %	94719
384	1190.7	0.37 %	177422
480	1182.3	0.33 %	363339

IV. CONCLUSIONS

In this paper, we have presented a MILP model to address the incorporation of investment decisions in recent elements, as EVs and ESS, which will have an important impact in the planning and expansion of future distribution networks.

We have proposed a clustering technique in order to correlate uncertain inputs associated to the stochastic nature of the problem. The scenarios are used in a decision making problem which determines the location of the facilities. Moreover, the EV charging demand has been modeled through a novel EV algorithm. The proposed methodology has been validated with a 54-node network.

We have shown how ESS can contribute to integrate renewable generation and EV charging demand in the coordinated expansion planning of a distribution network minimizing investment and operational costs, avoiding the need to expand the existing substations. Increasing the demand while reducing the energy costs outlines the potential of the combination of EVCS and ESS in distribution networks with a high penetration of renewables.

Future work will consider the possibility that EVs can inject power into the network when they are not in use. In addition, more generation technologies will be added to the model.

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Chapter 6

Reliability Assessment of Microgrids with Local and Mobile Generation, Time-Dependent Profiles, and Intra-Day Reconfiguration

Reliability Assessment of Microgrids with Local and Mobile Generation, Time-Dependent Profiles, and Intra-Day Reconfiguration

Pilar Meneses de Quevedo, *Member, IEEE*, Javier Contreras, *Fellow, IEEE*, Andrea Mazza, *Member, IEEE*, Gianfranco Chicco, *Senior Member, IEEE*, Radu Porumb, *Member, IEEE*

***Abstract*—In this paper, the notion of reliability assessment for distribution system applications is revisited to include a number of practices emerging in the smart grid context. The information on the variations in time of generation and demand is taken into account to establish a reference network configuration that considers the definition of an intraday reconfiguration strategy based on conventional load profiles for different categories of demand (residential, industrial, and commercial). After a fault, the service restoration process is aided by the formation of autonomous islanded subsystems (microgrids). During the restoration period, each subsystem is able to serve the local demand in a given portion of the network and to reconnect to the main network through proper synchronization. Dedicated solutions for mobile generation and storage are exploited to reach the nodes needing additional supply. A sequential Monte Carlo method is used to carry out reliability assessment. The use of this method incorporates the effects of interfering near-coincident faults and time-varying load and local generation patterns. The application on a real distribution network is presented, showing the probability distributions of the reliability indicators (power and energy not supplied), as well as the breakdown of these indicators for different demand categories.**

***Index Terms*—microgrid, reliability, smart grid, demand profile, mobile generation, intraday reconfiguration, resilience, sequential Monte Carlo.**

I. Introduction

MICROGRIDS are emerging as viable network structures to serve the local demand in the presence of an adequate local energy mix, able to provide voltage and frequency control and grid stability through the available resources during operation [1]. The concepts used to operate a microgrid can be adopted to determine how to manage an intentional island taken as a subsystem of a distribution network to obtain benefits during the restoration process after a fault [2]. In the same way, these concepts may be used to identify subsystems with self-healing capabilities, with the aim of enhancing the distribution system's resilience against extended service interruption events [3][4][5].

The classical reliability analysis of distribution systems is based on the calculation of a number of indicators taking into account the frequency and duration of the interruptions, for example, leading to the determination of the system availability, and the power and energy not supplied. Reliability indicators may be calculated either *a posteriori* (e.g., at the end of each year) in order to check the compliance with the regulatory limits set up by the relevant authority, or *a priori* (e.g., on the basis of the expected network operation for the next period) in order to be used as objective functions for single- or multi-objective optimization purposes [6] [7] [8], or within operational planning or expansion planning tools [9] [10][11][12].

In the classical *a priori* reliability analysis, the typical calculations were based on a number of hypotheses, generally considering a given network structure (i.e., the standard network configuration), given power for each customer (based on the contract power), and absence of contribution from local generation. Deterministic or probabilistic methods are used. The latter ones are of particular interest, as they provide information on the probability distributions of the reliability indices, making it possible to determine the exceeding probability of these indices with respect to specific limits.

Analytical methods or Monte Carlo (MC) methods may be used for probabilistic reliability analysis [13]. Analytical methods are faster [14]. An effective method that uses the characteristic functions is illustrated in [15]. A limitation of the analytical approach is that it cannot consider common-mode and interfering near-coincident faults. These limitations are not present in MC methods [16], in which the effects of multiple faults can be included, as well as dependencies on external variables and time-changing loads or generation. Different types of MC simulation include non-sequential methods with state sampling or state transition sampling [16], time sequential methods with state duration sampling, and pseudo-sequential MC methods with a non-sequential selection of the failure states and a sequential simulation of the sequence of neighboring states [17]. A recent proposal to represent correlated time series within a non-sequential method is discussed in [18].

The penetration of distributed energy resources (DER), including distributed generation (DG), distributed storage (DS) and demand response (DR), has raised interest in reliability assessment with DER, in particular with respect to the possibility of creating islands during the service restoration process, and also as an alternative to construct new network branches [19][20][21] [22]. A general overview of reliability models and methods for distribution systems with renewable energy DG is reported in [23]. An analytical formulation of reliability assessment with remote-controlled switches and islanded microgrids is presented in [24]. An analytical method that considers the DG reliability model, islanding operation and changes in the protection strategy is described in [25].

A non-sequential MC method is used in [26] to evaluate the reliability of active distribution grids. The application of the pseudo-sequential MC method is discussed in [27]. Examples of using the time-sequential MC method are reported in [28] to calculate the reliability indices for different DG applications without considering islanding, and in [29] with the possibility of forming islands for the generators placed downstream with respect to the fault. A two-step MC simulation is used in [30], where a number of new metrics for reliability assessment with microgrids are also introduced.

A specific case of using DS to improve reliability by considering both the customers' willingness to pay and the DS cost is presented in [31]. In [32] and [33] electric vehicles operating in vehicle-to-grid (V2G) mode are considered as a further possibility of enhancing reliability by exploiting the local supply located in parking lots. Centralized and dispersed contributions of electric vehicles including V2G and vehicle-to-home (V2H) are addressed in [34]. Furthermore, DR has the potential to improve service reliability during contingencies, provided that an appropriate plan for DR procurement is set up [35].

In a smart grid context, the evolution of distribution automation, DER control, computational methods and data analytics is making it possible to introduce a number of additional features into the classical reliability analysis tools. Thereby, reliability assessment is enriched with innovative contents such as:

- Incorporation of DER in the service restoration process, with the creation of intentional *islands*, provided that the technical properties of the DER are appropriate to ensure suitable control and stability of the microgrid;
- Provision of supply through *mobile* generation and storage, to add flexibility to the location of additional supply sources during the service restoration process;
- Possibility of considering *demand profiles* for different types of customers, that is, enabling the distinction among the interruptions occurring in different time periods for these customers;
- Change of network configurations over time, determining the most appropriate *intraday* configurations according to specific objective functions.

This paper shows how the above contents are included in reliability analysis, with the calculation of probabilistic reliability indices. In [36] a time-sequential MC simulation is presented for reliability evaluation of distribution systems with the presence of chronological patterns of specific renewable generation, using an intraday reconfiguration considering two optimal topologies for peak and off-peak hours. This paper is an extended and generalized version of [36]. The specific contributions are:

- Introduction of a set of conventional load profiles in the reliability analysis, in order to enable the determination of the *share* of energy not supplied (*ENS*) of the different types of consumers (e.g., residential, industrial and commercial) and local generation systems.
- Execution of a time-sequential MC simulation by considering the starting configuration resulting from the *intraday* reconfiguration carried out at fixed time intervals on the basis of the conventional load profiles.
- Formulation of a mathematical model for reliability assessment of a distribution system with renewable generation, possible formation of intentional islands, and use of *mobile* generation and storage systems.

The next sections of this paper are organized as follows. Section II recalls the reliability assessment methods used with DER and describes the emergent practices recently introduced in the smart grid context, which contribute to reliability assessment with new information. Section III reports the details of the reliability assessment procedure. Section IV shows the results of a case study of a real distribution network. The last section contains concluding remarks.

II. Emergent Practices in the Smart Grid Context

A. Conventional demand profiles in reliability analysis

Considering the same duration of the interruptions, the *ENS* of different types of customers changes when the interruption starts at different times of the day [37]. Indeed, more refined information may be found from a statistical assessment of the duration of the interruptions depending on the starting time of the interruption [38]. Reliability analysis techniques may be detailed by introducing the variation of the load patterns throughout time [39]. Hourly patterns of load and renewable energy sources are used in the analytical approach presented in [40]. The study presented in [41] concludes that the time dependency of the interruption cost should not be ignored, to avoid giving wrong cost signals in the regulation of the quality of supply.

Since the variation in time of the demand that would have been supplied to the loads without the interruption cannot be determined, a *conventional* rule has to be established to determine the *ENS* during an interruption, to be considered for different categories of customers. In this way, it is possible to calculate the *ENS* for each type of customer, and to determine the share of the overall *ENS* among them. For this purpose, different approaches may be considered:

a) *Traditional* approach, in which the rated power of the loads involved in the interruption is multiplied by the duration of the interruption to give the *ENS*. This approach cannot consider the time at which the interruption occurs.
b) *Load profile-based* approach, in which conventional predetermined load profiles constructed according to the category of consumers are applied to the duration of the interruption to determine the *ENS* for each category of consumers.
c) *Measure-based* approach, in which the active power of the load served at the time step before the occurrence of the fault is assumed as reference. With these bases, it is possible to determine the *ENS* by considering a constant power for the duration of the interruption, or to apply a combined approach based on the measured power and the loadprofile[1].

[1] The latter way to determine the *ENS* through the combination of the measured value with the load profile is not straightforward. A discussion on these aspects will be reported in a future contribution.

Of course, this approach is applicable only when the measured active power values are available at the time step preceding the interruption. A specific advantage is the possibility of dealing with individual loads and not only a customer category. In the absence of a totally metered system, in the realm of the evolution towards smarter grids, this approach could be applied only to the measured portion of the total load, keeping the other approaches mentioned above for the remaining part of the load.

B. Intraday reconfiguration

The recent trend towards extended automation in distribution networks and microgrids is making the idea of applying intraday reconfiguration more and more appealing. The variability in time of the load and generation patterns makes it possible to formulate suitable strategies to change the optimal network configuration during the day on the basis of a suitably defined objective function. Current literature has addressed the intraday reconfiguration problem under different points of view and time horizons, as summarized in [42]. Nevertheless, technical and practical issues limit the number of configuration changes that can be made during the day. Increasing the number of switching operations could result in more transient problems during switching, increased risk of outages, reduction in the expected life of the switches due to their extra stress, and higher cost of repeated switching. Furthermore, intraday reconfiguration leads to higher complexity in tracking the changes of the network configurations during time. A particular issue is the uncertainty whether the new configuration will be significantly better than the previous one, to make the reconfiguration action worthwhile. Resorting to a more extensive action of the centralized remote control of the switches is part of the main benefits of smart grids. However, this extensive action could raise vulnerability issues, as indicated in [43].

C. Exploitation of dedicated solutions for mobile generation and storage

The adoption of mobile generation technologies is one of the solutions that may be used by distribution companies in order to restore supply in a relatively flexible way, provided that efficient solutions for fault location are in place [44]. Depending on the size of the local generator to be used and the voltage level for network connection, the size of the mobile generation system changes. The technologies contain truck-mounted generators, transformers and protection systems with advanced interfaces to synchronize and control the generators [45]. The current trend is to develop technologies that may be mounted on an ordinary truck, in order to be ready to operate as fast as possible by making the travel time shorter. This aspect is crucial and limits the size of the mobile generation system. In fact, some mobile power stations available today are classified as “exceptional transports”, requiring special permits, additional auxiliary vehicles to follow the transport and, if needed, also to close some local roads to enable the transport. All these aspects increase the timing of on-site availability of the mobile generation considerably, strongly affecting the contribution of the mobile generation to reliability.

In addition to mobile generation, mobile storage is of interest for reliability purposes. The technical specifications for a substation-size lithium-ion energy mobile storage system, with rated values of 1 MW and 2 MWh, have been developed by a group of utilities [46]. From the technical point of view, mobile storage can be seen as a version of mobile generation with limited energy capacity.

The availability of mobile emergency power supply with generation and storage resources has to be properly coordinated in order to get the higher benefits from these resources. The solution strategies must also take into account the importance given to the network nodes [47]. The allocation of mobile generation vehicles is carried out in [48] by setting up a cost optimization algorithm that considers the investment costs of additional emergency supply, the customer outage cost, and the operation and maintenance cost of the emergency power supply systems. The pre-positioning of truck-mounted mobile emergency generators is proposed in [49] to dispatch these generators to some nodes of the distribution system with the aim of restoring critical loads, by forming multiple microgrids.

III. Reliability Assessment

A. Service restoration process

The proposed approach is designed to study real distribution systems, whose structural topologies are meshed, but the redundant branches are open to form radial configurations facilitating network operation and protection schemes. Each distribution network configuration is represented by the state (open/closed) of the connections of each branch terminal to its sending and ending nodes.

In this paper, two connecting devices are considered:

i) remote-controlled circuit breaker, with automatic trip in case of fault; and,
ii) remote-controlled synchronization device (switch), without automatic trip in case of fault.

The network structure is assumed to be known, without addressing the possible addition of feeder interties as in [50]. Furthermore, the optimal allocation of the switches is not addressed in this paper; the reader may refer to [51] for specific details.

Three types of faults are analyzed for calculating the duration of the interruptions, namely:

1. Faults at the *local generation units*, which may be multiple and may occur inside the restoration period from other faults. The local generating unit is excluded by the action of the local protection device. These faults only affect the availability of the local generation unit.
2. *Temporary faults* of the system branches with remote-controlled circuit breakers and with automatic trips. There is a single restoration stage, as, by definition, the fault is cleared after having reclosed the circuit breaker. When the circuit breaker located in the path from the terminal bus of the faulted branch to the root (substation) opens, all the downward nodes experience a temporary interruption. The local generators with fault ride-through capability remain connected; the other local generation units are switched off to avoid their negative impacts on fault currents and protection schemes.
3. *Permanent faults* of the system branches, indicating fault conditions still existing after the trip and first reclosing of

the circuit breaker. For these faults, remote-controlled operations and manual operations of the switches are performed, if necessary, to isolate the fault and restore the operation in the non-faulted part of the system. The circuit breaker initially opens the circuit, so the downstream feeder is de-energized. Then, the control center of the distribution system activates a remote controlled operation-based strategy exploring the faulted branch. With this strategy, the fault is located and the faulted branch is isolated. The loads of the feeder located upstream of the faulted branch are re-supplied, and for the loads downstream of the feeder there are two possibilities:

a) The supply to the loads is restored within the formation of an intentional island.
b) The loads are subject to a permanent interruption, with the exception of the nodes recovered by the *mobile* generation, until the reparation of the faulted branch has been completed.

The process after the fault reparation is completed with the restoration of the initial configuration. When the synchronization devices are present in the connection point, the islands can be reconnected to the distribution network without interruption. If there is no synchronization device in the connection point, it is necessary to disconnect the nodes located between the upstream node (able to perform synchronization) and the island boundary. In this case, there is an additional duration of the interruption, given by the time needed to reconnect the island to the grid. A suitable DG unit is needed to be able to sustain the island during and after the island formation, and its interface device must be able to identify the fault currents to avoid the island reconnection to the grid when a fault occurs inside the island.

Many factors affect the probability of the formation of an intentional island, namely:

i. Availability of local generators able to guarantee voltage/frequency control and dynamic response. In this respect, local generators operating in voltage-following mode (i.e., with no voltage control) are not suitable to support the islanding [52]. This may also happen for local generators aiming to provide voltage control, when they operate at their reactive power limits;
ii. Probability that the generation exceeds the load, providing an adequate supply, also taking into account the determination of the DER capacity under uncertain conditions [53]; and,
iii. Probability (1–*PIF*) of success in the transition to the island formation, where the probability of island formation (*PIF*) is an assigned probability of islanding failure. A further possibility could be to run a transient stability simulation for each island formation, to ensure that the new operating point in island conditions is correctly reached [54].

When the service has been restored, the island can be reconnected to the network only when synchronism between the island and the grid is reached at the connection interface.

[2] In some references, the negative binomial probability distribution has been considered instead of Poisson to represent the annual number of faults for MV cables [57][58].

B. Time-sequential Monte Carlo simulation approach

In classical reliability analysis, the Markov approach is used to establish analytical methods under the hypothesis that the times to failure and the repair times of the system components are exponentially distributed. In this case, the failure rates and the repair rates of these components are constant. However, the exponential distribution cannot be adopted for other variables such as the restoration times, for which various solutions have been adopted in literature, e.g., lognormal [55], normal [14], and Gamma [56] PDFs.

The time-sequential MC simulation is used to calculate the reliability indicators for a distribution system with DG. The procedure contains M repeated simulations, considering for each simulation a random fault pattern involving the network components and the DG units. The failure rate is specified for each component in the data input.

The overall period of time considered for the observation is denoted by T. Each simulation is based on a fault pattern that is generated by randomly extracting, for each component k, the number of faults, $n^{(k)}$, from a Poisson distribution using the failure rate as parameter[2]. Then, each fault $j = 1,\ldots, n^{(k)}$ involving each component k is randomly located in time period T by extracting a random number from a uniform probability distribution defined in time interval $[0,T]$ and using it to represent the time instant, $t_j^{(k)}$, at which the fault occurs.

At the end of the definition of the time instants for each fault, an ordered list is formed, containing all the time instants introduced in ascending order, to represent the time sequence of the fault events occurring in any component. Each fault instant is then associated with its restoration time, selected at random from the probability distribution (e.g., with a Gamma distribution) of the restoration time for the corresponding component. If the component is a branch, the selection includes the determination of whether the fault is temporary or permanent, with the related restoration times.

The definition of the fault pattern is followed by the analysis of the individual faults, one at a time, calculating the contribution of each fault to the reliability indicator considered, e.g., *ENS*. During the analysis, further aspects such as the availability and success of operation of the components called for performing specific actions (e.g., switching systems associated to DG units that have to operate to guarantee successful island creation) are considered. At the same time, possible multiple or dependent faults are handled during the analysis of the effects of the fault. Finally, the possible occurrence of another fault (set by the definition of the fault time instants), during the restoration process of the fault under analysis is verified. This occurrence is very unlikely, given the relatively fast restoration with respect to the overall time period of observation and the relatively low number of faults, but cannot be excluded for practical purposes.

C. Determination of the duration of the interruptions

Fig. 1 illustrates the characteristics of the computational procedure. The solution algorithm proceeds sequentially in time with respect to the chronological sequence of the interruption

events. The first action is the identification of the circuit breaker serving the faulted feeder. Then, the load points located in other feeders are supplied (with no interruption). For the faulted feeder, the procedure is based on the following steps:

1. Analysis of *temporary* faults: the first calculation is the extraction of the random restoration time. For the load points located in the feeder with an interruption, the duration of the interruptions is updated by adding the corresponding instant of the restoration time.
2. Analysis of *permanent* faults: the restoration process with the possibility of islanding formation is carried out. The following steps are considered:
   - For the faulted feeder, store the location of the load points in a list, and inspect which load point is assigned to an intentional island:
     - o find the local generators connected to the isolated nodes and check their availabilities at the moment when the fault occurs, and for the whole duration of the service restoration process (the local unit could be unavailable due to scheduled maintenance or to failure);
     - o for the load points assigned to an island, add the island formation time to the interruption duration;
     - o for the load points *not* assigned to an island, the interruption duration depends on the random restoration time. *Mobile* generation can be used to reach the non-supplied nodes: the interruption duration can be reduced, extracting a random number representing the time to activate the mobile generation.
   - If an island is formed, the power flow in the microgrid is calculated (e.g., with the backward-forward sweep method), and the constraints on the voltage and current limits verified. In the case of constraint violation, the structure of the intentional island is modified until no violation occurs [29]. All the load points belonging to intentional islands are marked as well as the DG units that control the island operation.
   - Identification of the synchronization points adjacent to the island, that may be:
     - a) located on the island boundary: no further contribution to the interruption duration;
     - b) not located on the island boundary: the island reconnection time is added to the interruption duration, due to the operations for restoring the initial configuration after the fault.
   - Finally, the possibility of using mobile generators to serve the non-supplied nodes is considered. The number of available mobile generators is randomly selected from 0 to a user-specified maximum number, with a given probability of the various occurrences. Instead of setting up a physical location for the mobile units when they are not used, the time to reach the node to supply is considered as the relevant random variable. The instances of this variable are extracted from a uniform distribution between a minimum and a maximum value.

[3] The optimal allocation of the switches is not addressed in this paper. The reader may refer to [51] for specific details.

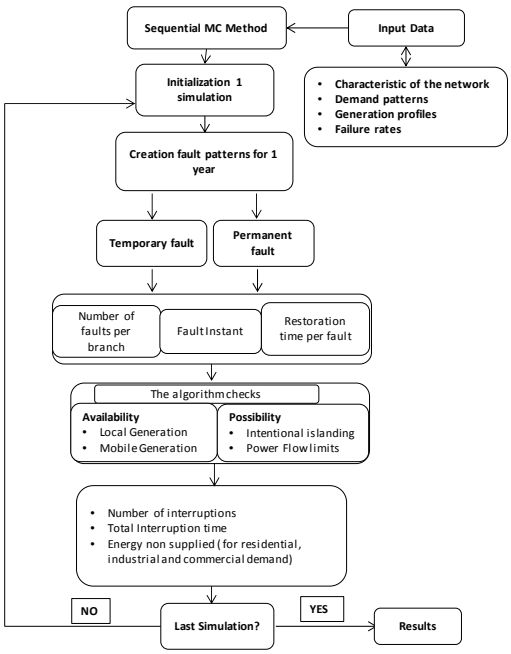

Fig. 1. Time-sequential MC reliability calculation method.

IV. Application to a Real Distribution System

A. Description of the system

A.1. Network structure

The medium-voltage (MV) distribution network under analysis is a real network with 207 nodes and 213 branches, located on an island. The network has a weakly meshed structure, but it is operated in a radial way. The number of redundant branches (open for obtaining a radial configuration) is 7. Furthermore, the system is supplied by a single thermal power plant, located at the slack node, composed of eight generator groups, with a total installed power of 20 MW [59]. The island is totally dependent on external sources of energy. The supply system is fed by diesel generators, as well as by oil-based ones.

The scheme of the network, where DG, circuit breakers and synchronization devices are located[3], is shown in Fig. 2. The big circle represents the slack node, while the small circles represent the other 206 nodes. The network contains different types of loads (residential, industrial, and commercial) and some DG plants supplied by wind, photovoltaic (PV), waste to energy (W2E) and geothermal systems, represented by colored squares. Hourly profiles are used to characterize the different types of loads and generations. The 7 redundant branches [42] are indicated in Table I, but are not drawn in Fig. 2 for the sake of simplicity.

For the one-year reliability assessment, the DG units have been included in the network to evaluate the benefits of the integration of renewable energy in isolated systems.

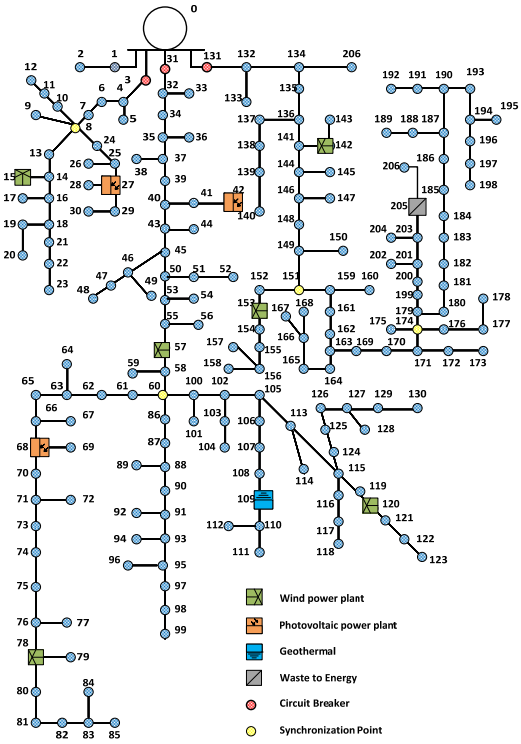

Fig. 2. Scheme of the MV network.

A.2. Generation profiles

The generation units considered are taken from [59]. The most realistic operation implies full exploitation of the geothermal and W2E sources and the inclusion of some wind and PV power plants. Geothermal and W2E profiles for one year are taken from [59] and [60]. The small geothermal power plant (2.5 MW) is located in the southwest of the island and operates during 8000 h/year (considering a programmed unavailability due to successive maintenance of the generation groups in winter).

Information on DG is reported in Table II. Wind and PV generation profiles are taken from historical data for one year available in [61]. In the case of wind, only data for 9 months are available, and the other 3 months are forecasted using a probabilistic method based on scenario generation from time series data, taken from the approach reported in [62].

TABLE I. REDUNDANT BRANCHES

Initial and final nodes of the 7 redundant branches						
2-69	4-131	8-135	23-148	73-121	85-198	73-121

TABLE II. DG CONNECTED TO THE NETWORK

Generation type	Number of units and rated power (kW)	Annual production (GWh)
Wind	2 x 20	0.15
PV	3 x 200	1.332
Geothermal	1 x 2500	19.99
W2E	1 x 370	1.91

A.3. Demand profiles

For distribution system studies, a relevant aspect is the characterization of the aggregate demand. The probabilistic model of the aggregate demand is very useful for system operators or aggregators for extracting information about the demand-side behavior in the operation of microgrids.

The time step used to scan the aggregate demand pattern is very important to preserve the information about the consumers' behavior and the related uncertainty. Conventional models of aggregate electrical demand consider an average value for a specific time step (e.g., 30 min to 60 min). In this case, one-hour step is used. The aggregate average load patterns for one day and for the whole network are illustrated in Fig. 3. In the same way, the power generation for a typical summer day is chosen in order to represent the generation profiles in Fig. 4.

A.4. Intraday configuration strategy

An intraday strategy is applied in order to maximize the optimality of the network configuration. In this case, two optimal configurations are used for the whole year, one for peak hours and another for off-peak hours, as shown in Table VII reported in [41]. These results have been found for the specific case with a relatively low penetration of DG. However, the method used is general, also in case of a more remarkable penetration of DG, in which the distinction between peak hours and off-peak hours becomes less evident.

A.5. Other data

For reliability analysis, the whole period of one year with time intervals of one hour is assumed. The failure rate per branch is 0.5 (for temporary faults) and 0.05 (for permanent faults). The duration of faults is assumed to be 10 s for temporary faults, and 3 min, 30 min, 1 h and 10 h for permanent faults, respectively. The fault probability of the generator is 0.1. The parameters of the restoration times for the Gamma distribution (shape and scale factor) are shown in Table III.

TABLE III. PARAMETERS FOR RESTORATION TIMES

Shape parameter (k)	Scale parameter (θ)	Approx. fault time
5	2	10 s
4	60	3 min
4	450	30 min
4	800	1 h
4	10000	10 h

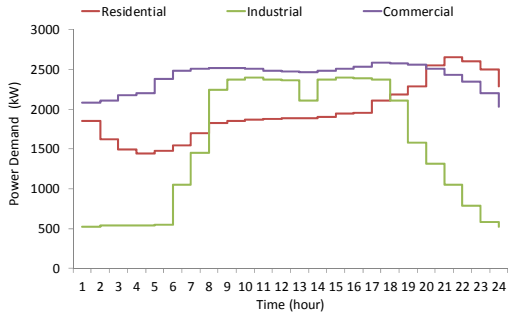

Fig. 3. Average hourly demand profiles.

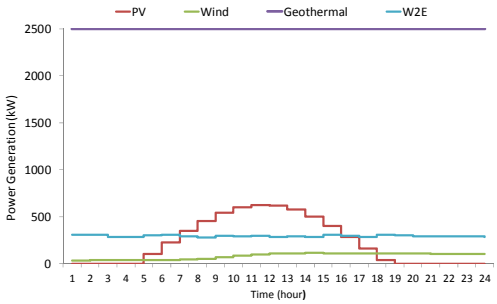

Fig. 4. Average hourly generation profiles for the summer period.

B. Results and discussion

B.1. Definition of the cases and simulation framework

The results of the reliability analysis are shown by applying the sequential MC method with 1000 repetitions in the following cases:

- Case I, with neither DG nor mobile generation;
- Case II, with mobile generation and no DG;
- Case III, with DG and no mobile generation;
- Case IV, with DG and mobile generation.

In all the cases, the same random faults are considered in order to provide a sound comparison among the differences in the *ENS* results.

The simulations have been carried out by using the CPLEX 11 solver in MATLAB [63]. An Intel Xeon E7-4820 computer with four processors at 2 GHz and 128 GB of RAM has been used.

B.2. Analysis of a specific simulation

The details of a specific simulation are provided here in order to illustrate how the algorithm process works. Let us analyze one permanent fault in branch 148 (connecting node 146 to node 148). The time of the fault is selected from a uniform distribution along the year; in this specific situation occurring during hour 19:00 of the 23rd day of the 9th month.

Initially, the circuit breaker located at node 131 is found and the downstream load (residential load 838.5 kW, industrial load 599.1 kW, and commercial load 867.7 kW) is not supplied. In that instant, the topology is the one shown in Fig. 5, the wind generator at node 153 is producing 12.8 kW, and the W2E power plant is generating 282.8 kW. The number of available mobile generators is 2, acting in the 42nd and 71st min, respectively, after the fault occurs.

After the algorithm finds the circuit breaker, it verifies the existence of local generation in the isolated feeder with suitable characteristics to create an intentional island, and looks for the synchronization point in order to isolate part of the network until the fault is restored.

There are two synchronization points at nodes 151 and 174. The wind generator at node 153 can only supply 12.8 kW of the demand (21.86 kW) at that node. On the other hand, the W2E power plant checks whether it can create an island supplying the loads near its location (node 205) with its own power. Therefore, there is an island formation between nodes 201, 203, 204, 205 and 206, located downstream from the synchronization point at node 174. In this specific situation, the synchronization point is not located on the island boundary. Finally, the existence of two available mobile generators covers the demand of nodes 148 and 149 until the fault is restored.

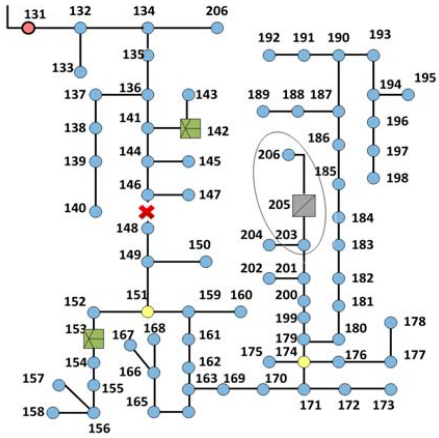

Fig. 5. Island formation during fault in branch 148.

B.3. Comparison criterion and overall results

Considering all the simulations for one year, for the sake of comparison, the faults are the same for all the cases. The maximum and minimum number of faults are 149 and 84, respectively. *ENS* values have been calculated for residential, industrial and commercial users. However, the total energy consumption in one year for the three types of users is different. Considering the conventional load profiles established for the different types of users, the energy consumption in one year (without interruptions) is 17,275 MWh for residential users, 13,346 MWh for industrial users, and 21,073 MWh for commercial users. Thereby, considering only the *ENS* values to compare the results for the different users is not appropriate. The energy consumption is taken as the conventional reference to calculate the *ratio* between the total *ENS* and the contract power for each type of user. This ratio is the relevant variable used for the sake of comparison.

The Cumulative Distribution Functions (CDFs) of the *ENS* to contract power ratio are represented in Figs. 6, 7 and 8, respectively, in the four cases. Comparing the three figures, it

is more likely to have a higher *ENS* to contract power ratio for the commercial users, compared to the other ones, as its CDF is shifted to the right-hand side. On the other hand, it is more frequent to have a lower *ENS* to contract power ratio, first, for the industrial users, then for the residential users and, finally, for the commercial users, as shown in the figures below. Moreover, as expected, there is a higher probability to have a lower *ENS* in Case IV, which includes DG and availability for mobile generation. Cases II and III are similar, Case III being slightly better to reduce the overall *ENS.* Finally, Case I is the worst one in terms of continuity of supply. As observed, the CDF is close to 1 in the worst situation, when the ratio is 28 h for industrial users, 31 h for residential users and 39 h for commercial users. This can also be seen in Fig. 9. Moreover, this figure also illustrates the different total *ENS* values corresponding to the different methods. The traditional approach provides higher *ENS*, as expected, while the results obtained from the measure-based and load profile-based approaches are very similar. In particular, the load profile-based approach leads to slightly lower values than the measure-based approach, whilst being more accurate in determining the total *ENS*.

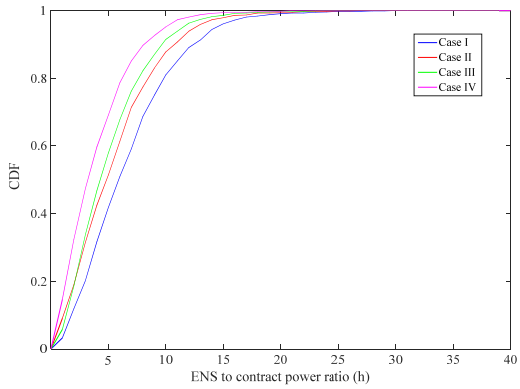

Fig. 6. CDF of the *ENS* to contract power ratio for residential users.

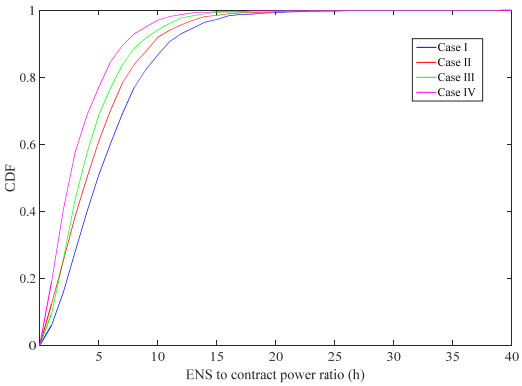

Fig. 7. CDF of the *ENS* to contract power ratio for industrial users.

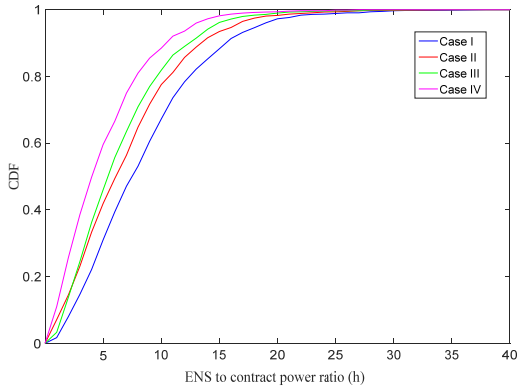

Fig. 8. CDF of the *ENS* to contract power ratio for commercial users.

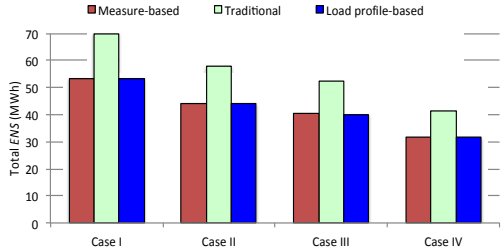

Fig. 9. Average values of the total *ENS* in the four cases.

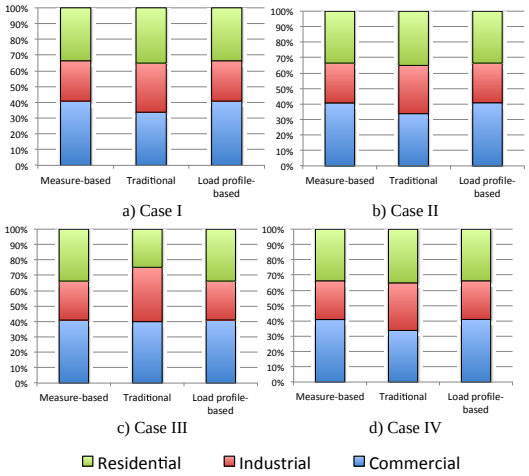

Fig. 10. *ENS* share for residential, industrial and commercial users with different approaches to *ENS* calculation and DG and mobile generation penetration.

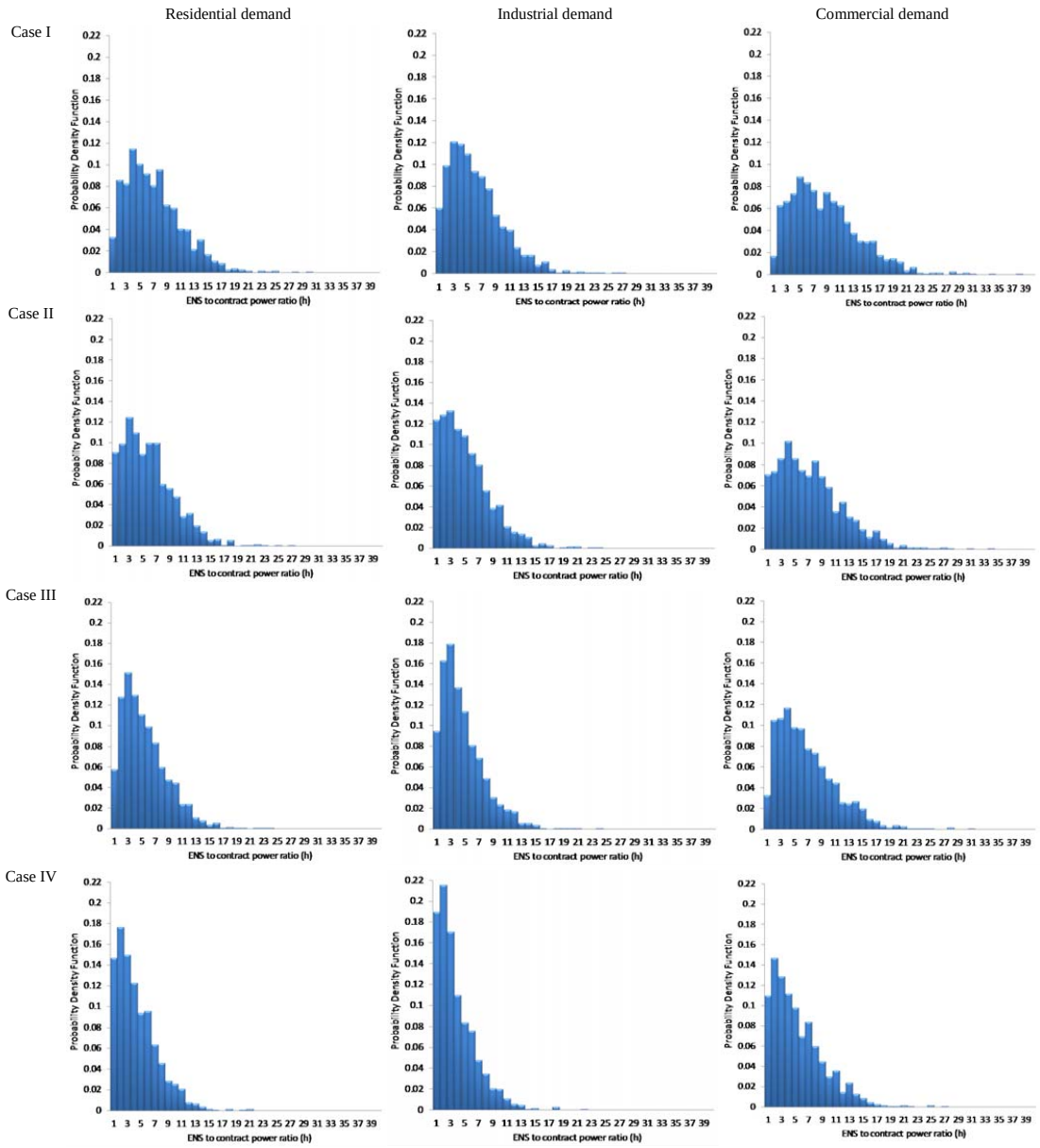

Fig. 11. Probability Density Functions (PDFs) of the *ENS* to energy consumption ratio.

Fig. 10 illustrates the *ENS* share among the different users for each case. The *ENS* share for the commercial users is similar to the measure-based and load profile-based approaches for all the cases. In the traditional approach, the *ENS* share is equivalent among the three types of users, except for Case III, in which the proportion is 40% commercial, 35% industrial and 25% residential, the *ENS* share of the residential users being the lowest of all the cases. In the load profile-based and measure-based approaches, the *ENS* share remains

approximately constant among all the users for the 4 cases (41% commercial, 25% industrial and 34% residential). Finally, as explained before, the higher percentage of the *ENS* share corresponds to the commercial users.

Fig. 11 displays the Probability Distribution Functions (PDFs) of the *ENS* to contract power ratio. It shows that the commercial demand contribution to the *ENS* to contract power ratio is also higher than for the residential and industrial users, as it is further shifted to the right for the four cases. The highest probability is 0.21 in Case IV for the industrial users, which corresponds to an *ENS* to contract power ratio of 2 hours. This means that the highest probability of having the lowest ratio is for the industrial users. In fact, the probability of having a lower ratio is seen in Case IV, in which the PDFs are concentrated on the lowest ratios for all types of users. In all the cases the distribution is asymmetrical and right-skewed.

V. Conclusions

This paper has presented an extended framework for the reliability evaluation of active distribution systems for a period of time. This framework includes the possibility of creating intentional islands in case a fault occurs, and show how the introduction of DG, intraday network reconfiguration strategy and mobile generation improve reliability by reducing the *ENS*.

The effectiveness of the proposed approach has been shown in the application to a real MV network. Numerical results have been presented in different cases, with and without DG and mobile generation, and with different ways to calculate the *ENS*, based on conventional load profiles or measured values of the demand at given time steps. This is in line with the current developments aimed at providing practical implementations of the smart grid paradigm. One of the advantages that DG can provide to electric utilities and customers is the possibility of improving the continuity of supply by implementing safe intentional islands in the event of an upstream supply outage. The possibility of creating islands during the service restoration process may be constrained by regulatory issues, as the DG owner would have to take care of the loads served by another entity in normal operating conditions. The analyses carried out in this paper consider that such a limitation is not in place.

Based on the framework presented, it is possible to carry out many types of parametric analyses by changing the amount of DG and mobile generation in the network, assessing the effects on reliability in such a way to provide useful information for distribution system planning.

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Chapter 7

Summary, Conclusions, Contributions and Future Works

This chapter presents the summary of this dissertation, the main conclusions, contributions and possible future work.

7.1 Summary

This thesis deals with new operation and planning models for future distribution networks allowing for a growing penetration of RES with an optimal integration of generic ESS and EV in the distribution system. It aims to establish new management tools in the recent energy framework optimizing operation and investment in network assets, DG and upcoming devices like generic ESS and EVCS.

The main research lines of this thesis have been the following:

1. **Real-Time Operation Tools**
   Contingency Assessment and Distribution Network Reconfiguration in Distribution Grids Including Wind Power and Energy Storage

   Islanding in Distribution Systems Considering Wind Power and Storage

   These two works use two-stage stochastic real-time operation models with wind power generation and storage devices.
   The first one deals with the reconfiguration of the distribution network in order to overcome the impact of outages under an N-1 contingency condition and increase of power losses. An exhaustive analysis has been performed for all the outages with the possibility of having isolated radial grids.

The second work presents a model in order to maximize load and generation balance under islanded conditions with additional constraints for reactive power. The output of the mathematical model has been analyzed using 9 cases in 3 islanded areas.

2. **Medium-Term Operation Planning Tool**
   Optimal Placement of Energy Storage and Wind Power under Uncertainty

   This research proposes a stochastic model with a detailed alternative current optimal power flow that uses binary variables to define the location of wind generation and storage. The results show the performance of the model under different values of installed ESS and wind capacities in a given distribution network.

3. **Long-Term Planning Tool**
   Impact of Electric Vehicles on the Expansion Planning of Distribution Systems Considering Renewable Energy, Storage and Charging Stations

   This work presents a stochastic multistage distribution expansion planning model where investments in distribution network assets, RES, ESS and EVCS are jointly considered. The target of the DSO is to minimize the generation and network investment costs while meeting the demand. The outcomes of the model are the locations and sizes of RES, ESS, EVCS and the distribution assets to be installed, reinforced or placed.

4. **Reliability Assessment Tool**
   Reliability Assessment of Microgrids with Local and Mobile Generation, Time-Dependent Profiles, and Intra-Day Reconfiguration

   The use of a sequential MC method is used to accomplish a reliability evaluation of the microgrid. Dedicated solutions for mobile generation and storage are exploited considering an intraday reconfiguration strategy. An application to a real distribution network is presented, showing the probability distributions of the ENS, as well as the breakdown of these indicators for different demand categories (residential, industrial, and commercial). This framework includes the possibility of creating intentional islands in case a fault occurs, and shows how the introduction of DG, intraday network reconfiguration strategies and mobile generation improve reliability by reducing the ENS.

7.2 Conclusions

The focus of this thesis has been to develop tools that manage the optimal operation and planning of the new distribution networks associated to the increasing penetration of RES and the integration of new energy sources. The main conclusions related to each of the papers published are presented below:

1. The most relevant conclusions of the paper entitled "Contingency Assessment and Distribution Network Reconfiguration in Distribution Grids Including Wind Power and Energy Storage" are:

   (a) The advantages of having ESS and renewable energy in terms of real-time operation under N-1 contingencies in distribution networks have been demonstrated.

   (b) The penetration of ESS and wind power generation has improved grid operation by reducing power losses. In addition, in case of contingencies, ESS has decreased the need for generation curtailment.

   (c) The method improves reliability by allowing optimal radial reconfiguration and radial islanded operation if required.

   (d) There is a reduction of cost in the system energy losses and in the cost of the energy supplied by the substation.

   (e) The proposed model can be a valuable tool for an electrical distribution company to optimally reconfigure the system by evaluating all possible contingencies of the network using wind power and ESS.

2. The conclusions related to the paper entitled "Islanding in Distribution Systems Considering Wind Power and Storage" are:

   (a) The proposed model has led to the correct operation of the grid in islanded situations and has avoided a complete blackout in these areas under different levels of generation and demand.

   (b) The combination of wind generation and ESS leads to having more load and generation under islanded conditions.

   (c) The generation is able to compensate the reactive power after islanding formation. Reactive power has been introduced as a limitation in the optimization model.

   (d) It is possible to reconfigure the network by opening and closing the switches that exist within each island, optimizing their operation.

3. The most important conclusions of the paper entitled "Optimal Placement of Energy Storage and Wind Power under Uncertainty" are:

   (a) The proposed MILP model is well suited to find the best locations and sizes for wind units and ESS. It is also desirable to have ESS with a high maximum value of production or storage power because the device has less charging or discharging restrictions when required by the network.

   (b) The total operating costs has been reduced with the combination of the technologies mentioned above, mainly since wind curtailment costs are reduced. The wind limitation is part of the operation procedures that the DSO must apply for system security reasons in situations where there is no energy storage in operation.

4. The conclusions related to the paper entitled "Impact of Electric Vehicles on the Expansion Planning of Distribution systems Considering Renewable Energy, Storage and Charging Stations" are:

   (a) It has been shown how ESS can contribute to integrate renewable generation and EV charging demand in the coordinated expansion planning of a distribution network.

   (b) Investment and operating costs have been minimized, thus avoiding the need to expand the existing substation.

   (c) Increasing the demand while reducing the energy costs outlines the potential of the combination of EVCS and ESS in distribution networks with a high penetration of renewables.

5. The most important conclusions of the paper entitled "Reliability Assessment of Microgrids with Local and Mobile Generation, Time-Dependent Profiles, and Intra-Day Reconfiguration" are:

   (a) One of the advantages that DG can provide to electric utilities and customers is the possibility of improving the continuity of supply by implementing safe intentional islands in the event of an upstream supply outage.

   (b) The possibility of creating islands during the service restoration process may be constrained by regulatory issues, as the DG owner would have to take care of the loads served by another entity in normal operating conditions.

   (c) It has been possible to carry out many types of parametric analyses by changing the amount of DG and mobile generation in the network, assessing the effects on reliability in such a way to provide useful information for distribution system planning.

7.3 Contributions

The main contributions of the thesis are presented below:

1. From a methodological perspective, stochastic mixed-integer linear programming has been used in the optimization models included in this thesis to consider the intermittency of renewable energy. Additionally, in the contingency and islanding tool, a two-stage stochastic mixed-integer linear programming model has been developed as there are some decisions that do not depend on the scenario. The multiobjective stochastic mixed-integer linear programming method introduced for the optimization models provides some benefits: a) the mathematical model is robust, b) the computational behavior of a linear solver is more efficient than those of nonlinear solvers, providing a global optimal solution, and c) convergence can be guaranteed using classical optimization techniques. Different methods have been applied to create scenarios depending on the period of time covered and the purpose of each model.

2. From a modeling perspective, a joint programming model of the optimal reconfiguration and contingency assessment has been carried out for a distribution system. Furthermore, a joint expansion planning optimal tool has been developed to stress the relevance of integrating ESS in investment models under the increasing penetration of RES and the upcoming integration of EV under uncertainty. Moreover, the formulation of a mathematical model for reliability assessment of a distribution system with renewable generation, with the possibility of considering demand profiles for different types of customers, possible formation of intentional islands, change of network configurations over time, and use of mobile generation and storage systems has been presented.

3. In order to account for the future smart distribution systems, the integration of the main energy sources has been a subject of study in this thesis. The availability of ESS, the integration of RES, as well as the growing number of EV have been analyzed in the management of the operation and planning models shown.

4. The full publication list in ISI-indexed journals is presented below.

   Publications in ISI-indexed journals

   - P. Meneses de Quevedo, J. Contreras, M.J. Rider, J. Allahdadian, "Contingency Assessment and Network Reconfiguration in Distribution Grids Including Wind Power and Energy Storage," *IEEE Transactions on Sustainable Energy*, vol. 6, no. 4, pp. 1524–1533, Oct. 2015. Digital Object Identifier: 10.1109/TSTE.2015.2453368.
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   - P. Meneses de Quevedo, G. Muñoz-Delgado and J. Contreras, "Impact of Electric Vehicles on the Expansion Planning of Distribution Systems Considering Renewable Energy, Storage and Charging Stations," *IEEE Transactions on Smart Grid*, in press, Sept. 2017. Digital Object Identifier: 10.1109/TSG.2017.2752303.
   - P. Meneses de Quevedo, J. Contreras, A. Mazza, G. Chicco and R. Porumb, "Reliability Assessment of Microgrids with Local and Mobile Generation, Time-Dependent Profiles, and Intra-Day Reconfiguration," *IEEE Transactions on Industry Applications*, in press, Sept. 2017. Digital Object Identifier: 10.1109/TIA.2017.2752685.
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Other Publications

- P. Meneses de Quevedo, J. Alladadian, J. Contreras, G. Chicco, "Islanding in Distribution Systems Considering Wind Power and Storage," *Sustainable Energy, Grids and Networks*, vol. 5, pp. 156-166, March 2016. Digital Object Identifier: 10.1016/j.segan.2015.12.002.

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- P. Meneses, J. Contreras, "An Economic and Regulatory Framework for Insular Grids: The Case of the Canary Islands," 2015 12th International Conference on the European Energy Market (EEM), Lisbon, 19-22 May 2015, Digital Object Identifier: 10.1109/EEM.2015.7216684.
- A.W. Bizuayehu, A.A. Sánchez de la Nieta, J.P.S. Catalão, P. Meneses de Quevedo, J. Contreras, "Distribution System Reconfiguration in Economic Dispatch with High Wind Penetration," IEEE Power Energy Society General Meeting, Denver, 26-30 Jul 2015, Digital Object Identifier: 10.1109/PESGM.2015.7286251.
- A.W. Bizuayehu, A.A. Sánchez de la Nieta, J.P.S. Catalão, P. Meneses de Quevedo, J. Contreras, "Distribution System Short-term Operation Loss Analysis with Stochastic Wind Integration," IEEE PowerTech, Eindhoven, 29 Jun- 2 Jul 2015, Digital Object Identifier: 10.1109/PTC.2015.723240.
- P.Meneses de Quevedo, J. Contreras, A. Mazza, G. Chicco and R. Porumb, "Modeling and Reliability Assessment of Microgrids Including Renewable Distributed Generation," IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC), Florence, 7-10 Jun 2016, Digital Object Identifier: 10.1109/EEEIC.2016.7555659.
- P. Meneses de Quevedo, G. Muñoz-Delgado and J. Contreras, "Joint Expansion Planning of Distribution Networks, EV Charging Stations and Wind Generation Under Uncertainty," IEEE Power Energy Society General Meeting, Chicago, 16-20 Jul 2017.

Books

- J. Contreras, M. Asensio, P. Meneses de Quevedo and G. Muñoz-Delgado, "Joint RES and Distribution Network Expansion Planning under a Demand Response Framework," 2016, Academic Press, ISBN 978-0128053225.

Book Chapters

- M. Asensio et al., "Smart and Sustainable Power Systems: Operations, Planning, and Economics of Insular Electricity Grids, Chapter 6: Electric Price Signals, Economic Operation, and Risk Analysis," edited by João P.S. Catalão, pages 285-344, 2016, CRC PRESS, ISBN 978-1-4987-1212-5.

Poster contributions

- P. Meneses, J. Contreras, "Technical and Economic Impact of Integrating EV in an Insular Distribution Grid," 23rd International Conference on Electricity Distribution (CIRED), Lyon, 15-18 Jun 2015.
- P. Meneses, J. Contreras, "Modeling and Reliability Assessment of Microgrids Including Renewable Distributed Generation," VI Jornadas Doctorales de la UCLM, Toledo, 18 Oct 2016.

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- P. Meneses de Quevedo et al., "Deliverable 6.1. Economic Framework of Insular Electric Networks," SiNGULAR project.
- P. Meneses de Quevedo et al., "Deliverable 6.2. Report on the Scenario Analysis for the Insular Electricity Grids and Development Completed for Risk Analysis Tools," SiNGULAR project.

7.4 Future Works and Open Problems

The research work presented in this thesis could be susceptible to several improvements. More generation technologies could be added to the model like biomass, cogeneration, hydro or thermal solar. In this way, the modeling of new sources of DG that have not been included in this thesis could be subject to further study.

Moreover, distribution networks evolve from traditional passive networks to active networks being capable of integrating the behaviour and actions of all users connected to it, generators, consumers and operators in an intelligent way. Therefore, it is expected that this new context will take advantage of the active participation of consumers, the integration of ESS and the incorporation of EV. Accordingly, new methodologies should include demand response and new information management tools like intelligent monitoring, control techniques and intelligent communication.

Future works will consider the possibility that EV can inject power into the network when they are not in use in both operation and expansion planning optimization models. Thus, the development of models based on multi-level programming in the expansion of distribution networks and generation is proposed. The different levels could include the minimization of the expansion planning cost, the

minimization of consumer payment, the minimization of the charging cost for the users of EV and the maximization of the profit of the users of EV when injecting power into the network.

Another interesting topic that could be implemented in both operation and planning models is meshed operation, in order to take advantage of the increasing penetration of DG. This must consider a protection system that would be required for this meshed network configuration with the main purpose of operating it successfully. Therefore, the expansion planning model could integrate bidirectional flows for future research.

The evolution of distribution automation is creating opportunities for changing the network configuration across time, in particular for microgrids and newly developed networks in small energy districts. The interest of changing the network configuration in certain periods comes from the fact that, after the introduction of suitable configuration changes, the system losses (and their costs) can decrease significantly with time-varying load and local generation patterns.

Technology developments decreasing the cost of renewable sources and EV will take place in the future. Recently, RES are being connected to distribution grids at an extraordinary rate, consumers are installing solar panels on their roofs, new market players are starting to sell flexibility services, and EV are starting to appear on the roads. All of these are impacting electricity systems, notably DSO and the way they operate and develop their grids leading them to adapt and innovate. Recommendations regarding system planning and operation, additional cooperation and coordination between transmission system operators and DSO will be studied in the future.

Finally, the uncertainty modeling presented in this thesis can be extended by applying robust optimization and adaptive robust optimization in order to model the uncertainty sources of distribution system operation and planning.

Chapter 8

Conclusiones de la Tesis

El objetivo de esta tesis doctoral ha sido desarrollar herramientas que gestionen la operación y la planificación de las nuevas redes de distribución asociadas a una creciente penetración de fuentes de energía renovable y la integración de nuevas fuentes de energa.

A continuación se presentan las principales conclusiones relacionadas con cada uno de los trabajos publicados:

1. Las conclusiones más relevantes del artículo titulado "Contingency Assessment and Distribution Network Reconfiguration in Distribution Grids Including Wind Power and Energy Storage" son:

   (a) Se ha demostrado la ventaja de tener conjuntamente unidades de almacenamiento de energía y energías renovables, en términos de operación en tiempo real bajo contingencias N-1 en redes de distribución.

   (b) La penetración de los dispositivos de almacenamiento y de generación eólica ha mejorado el funcionamiento de la red reduciendo las pérdidas de energía. Además, en el caso de contingencias, los sistemas de almacenamiento han disminuido la reducción en la producción de generación eólica.

   (c) Este método mejora la fiabilidad permitiendo una óptima reconfiguración de forma radial y una operación radial en isla, si fuese necesario.

   (d) Hay una reducción en el coste de las pérdidas del energía del sistema y en el coste de la energía suministrada por la subestación.

   (e) El modelo propuesto puede ser una herramienta valiosa para que una empresa de distribución eléctrica pueda reconfigurar el sistema de forma óptima evaluando todas las posibles contingencias de la red utilizando la energía eólica y los sistemas de almacenamiento de energía.

2. Las conclusiones relacionadas con el artículo "Islanding in Distribution Systems Considering Wind Power and Storage" son:

(a) El modelo propuesto ha llevado a un correcto funcionamiento de la red en situaciones aisladas y ha evitado un apagón completo en estas áreas bajo diferentes niveles de generación y demanda.

(b) La combinación de generación eólica y sistemas de almacenamiento de energía permite mantener el balance de carga y de generación bajo condiciones de isla.

(c) La generación es capaz de compensar la potencia reactiva después de la formación de la isla. La potencia reactiva se ha introducido como una limitación en el modelo de optimización.

(d) Se posibilita la reconfiguración, abriendo y cerrando los interruptores que existen dentro de cada isla, optimizando su funcionamiento.

3. Las conclusiones relacionadas con el artículo "Optimal Placement of Energy Storage and Wind Power under Uncertainty" son:

   (a) El modelo de programación lineal entera mixta es muy adecuado para encontrar la mejor ubicación y el mejor tamaño para las unidades de viento y sistemas de almacenamiento de energía. También es deseable tener un sistema de almacenamiento con un alto valor máximo de potencia de producción o almacenamiento, porque el dispositivo está menos restringido para cargarse o descargarse cuando la red lo requiera.

   (b) Los costes operativos totales han sido reducidos con la combinación de estas tecnologías mencionadas anteriormente, principalmente en este tipo de modelos se reducen los costes de reducción del viento. La limitación del viento forma parte de los procedimientos de operación que el operador de la red de distribución tiene que cumplir por razones de seguridad del sistema en situaciones donde no haya sistemas de almacenamiento de energía funcionando.

4. Las conclusiones relacionadas con el artículo titulado "Impact of Electric Vehicles on the Expansion Planning of Distribution Systems Considering Renewable Energy, Storage and Charging Stations" son:

   (a) Se ha demostrado cómo los sistemas de almacenamiento genéricos pueden contribuir a integrar la generación renovable y la demanda de carga de los vehículos eléctricos en la planificación de la expansión coordinada de una red de distribución.

   (b) Los costes de inversión y operación han sido minimizados, evitando así la necesidad de ampliar las subestaciones existentes.

   (c) Aumentar la demanda y reducir los costes energéticos esboza el potencial de la combinación de las estaciones de carga de los vehículos eléctricos y los sistemas de almacenamiento de energía en las redes de distribución con una alta penetración de energías renovables.

5. Las conclusiones más importantes del artículo titulado “Reliability Assessment of the Microgrids with Local and Mobile Generation, Time-Dependent Profiles, and Intra-Day Reconfiguration” son:

   (a) Una de las ventajas que la generación distribuida puede proporcionar a las empresas de electricidad y a los clientes es la posibilidad de mejorar la continuidad de suministro mediante la implantación de islas intencionales seguras en caso de una interrupción del suministro en sentido ascendente.

   (b) La posibilidad de crear islas durante el proceso de restauración del servicio puede verse restringida por cuestiones regulatorias, ya que el propietario de la generación distribuida tendría que ocuparse de las cargas suministradas por otra entidad en condiciones normales de funcionamiento.

   (c) Se han podido llevar a cabo muchos tipos de análisis paramétricos cambiando la cantidad de unidades de generación distribuida y de generación móvil en la red, evaluando los efectos sobre la fiabilidad, de tal manera que proporcionen una información útil para la planificación del sistema de distribución.

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