Impacts of Optimal Energy Storage Deployment and Network Reconfiguration on Renewable Integration Level in Distribution Systems

Sérgio F. Santos[a], Desta Z. Fitiwi[a,b], Marco R. M. Cruz[c], Carlos M. P. Cabrita[d], and João P. S. Catalão[a,c,e*]

[a] C-MAST, University of Beira Interior, R. Fonte do Lameiro, 6201-001 Covilhã, Portugal
[b] University Pontificia Comillas, R. Calle Alberto Aguilera, 23, 28015 Madrid, Spain
[c] INESC TEC and Faculty of Engineering of the University of Porto, R. Dr. Roberto Frias, 4200-465 Porto, Portugal
[d] CISE, University of Beira Interior, R. Fonte do Lameiro, 6201-001 Covilhã, Portugal
[e] INESC-ID, Instituto Superior Técnico, University of Lisbon, Av. Rovisco Pais, 1, 1049-001 Lisbon, Portugal

Abstract

Nowadays, there is a wide consensus about integrating more renewable energy sources—RESs to solve a multitude of global concerns such as meeting an increasing demand for electricity, reducing energy security and heavy dependence on fossil fuels for energy production, and reducing the overall carbon footprint of power production. Framed in this context, the coordination of RES integration with energy storage systems (ESSs), along with the network's switching capability and/or reinforcement, is expected to significantly improve system flexibility, thereby increasing the capability of the system in accommodating large-scale RES power. Hence, this paper presents a novel mechanism to quantify the impacts of network switching and/or reinforcement as well as deployment of ESSs on the level of renewable power integrated in the system. To carry out this analysis, a dynamic and multi-objective stochastic mixed integer linear programming (S-MILP) model is developed, which jointly takes the optimal deployment of RES-based DGs and ESSs into account in coordination with distribution network reinforcement and/or reconfiguration. The IEEE 119-bus test system is used as a case study. Numerical results clearly show the capability of ESS deployment in dramatically increasing the level of renewable DGs integrated in the system. Although case-dependent, the impact of network reconfiguration on RES power integration is not significant.

Keywords: Energy storage; distributed generation; network reinforcement; network switching; renewable energy sources; stochastic mixed integer linear programming.

Nomenclature

Sets/Indices

$g/\Omega^g/\ \Omega^{DG}$	Index/set of generators/DGs
k/Ω^k	Index/set of branches
s/Ω^s	Index/set of scenarios
t/Ω^t	Index/set of time stages
w/Ω^w	Index/set of snapshots

* Corresponding author at the Faculty of Engineering of the University of Porto, R. Dr. Roberto Frias, 4200-465 Porto, Portugal.
E-mail address: catalao@ubi.pt.

$\varsigma/\Omega^{\varsigma}$ Index/set of substations

Parameters

$ER_{g}^{E}, ER_{g}^{N}, ER_{\varsigma}^{SS}$ Emission rates of existing and new DGs, and energy purchased, respectively (tCO_2e/MWh)

$IC_{g,i}$, IC_{k}, IC_{tr}, $IC_{es,i}$ Investment cost of DG, line, transformer and energy storage, respectively (M€)

$LT_{es}, LT_{g}, LT_{k}, LT_{tr}$ Lifetimes of energy storage, DG, distribution line, and transformer system, respectively (years)

MC_{es}^{E}, MC_{es}^{N} Maintenance cost of existing / new storage per year (M€)

MC_{g}^{E}, MC_{g}^{N} Maintenance costs of existing and new DGs (M€/yr)

MC_{k}^{N}, MC_{k}^{E} Maintenance cost of new and existing line (M€/yr)

MC_{tr}^{N}, MC_{tr}^{E} Maintenance cost of new/existing transformer per year (M€)

$OC_{g,i,s,w,t}^{E}, OC_{g,i,s,w,t}^{N}$ Operation cost of unit energy production by existing and new DGs (€/MWh)

$\eta_{ch,es}, \eta_{dch,es}$ Charging/discharging efficiency

$\lambda_{s,w,t}^{CO_2e}$ Price of emissions (€/tons of CO_2 equivalent)

$\lambda_{s,w,t}^{es}$ Variable cost of energy storage (€/MWh)

$\lambda_{s,w,t}^{\varsigma}$ Price of electricity purchased (€/MWh)

μ_{es} Scaling factor

ρ_{s}, π_{w} Probability of scenario *s* and weight (in hours) of snapshot group *w*

$\upsilon_{s,w,t}$ Penalty for unserved power (€/MW)

Variables

$D^{i}_{s,w,t}$	Active power demand at node *i* (MW)
$E_{es,i,s,w,t}$	Reservoir level of ESS (MWh)
$I^{ch}_{es,i,s,w,t}, I^{dch}_{es,i,s,w,t}$	Charging/discharging indicator variables
$P^{ch}_{es,i,s,w,t}, P^{dch}_{es,i,s,w,t}$	Charged/discharged power (MW)
$P^{E}_{g,i,s,w,t}, P^{N}_{g,i,s,w,t}$	Active power produced by existing and new DGs (MW)
$P_{k,s,w,t}$	Power flow through branch *k* (MW)
$P^{SS}_{\varsigma,s,w,t}$	Active power imported from grid (MW)
$u_{g,i,t},\ u_{k,t}$	Utilization variables of existing DG and lines
$x_{g,i,t},\ x_{es,i,t},\ x_{k,t},\ x_{tr,ss,t}$	Investment variables for DG, storage systems, transformer and distribution lines, respectively
$\delta_{i,s,w,t}$	Unserved power at node *i* (MW)
$\varphi_{k,s,w,t}$	Losses associated to each feeder (MW)

Functions

EC^{DG}_{t}	Expected cost of energy from DGs (M€)
EC^{ES}_{t}	Expected cost of energy from energy storage (M€)
EC^{SS}_{t}	Expected cost of energy purchased from upstream (M€)
$EmiC^{DG}_{t}$	Expected emission cost of DG power production (M€)
$EmiC^{N}_{t}, EmiC^{E}_{t}$	Expected emission cost of power production using new and existing DGs, respectively (M€)

$EmiC_t^{SS}$	Expected emission cost of purchased power (M€)
$ENSC_t$	Expected cost of unserved power (M€)
$InvC_t^{DNS}$, $MntC_t^{DNS}$	NPV investment/maintenance cost of DNS components (M€)

1. Introduction

1.1. Background and Motivations

Driven by a number of technical, economic and structural factors, the integration of renewable energy sources (RESs) is gaining an unprecedented momentum in many countries all over the world. In other words, the level of RESs integrated in power systems is increasing worldwide. Some of the main reasons that explain the massive integration of RESs are the continuous growth of energy consumption worldwide, the environmental issues associated with energy production (pollutant and inefficient production practices) and the climate change concerns [1], [2]. Policy makers in many states across the globe are setting forth ambitious RES integration targets [3]. This is expected to reduce the energy production from conventional sources such as oil, gas and coal, which currently provide about 80% of primary energy worldwide according to the report in [4]. Despite the increasing trend of RES developments, mainly wind, solar and geothermal, their share in the primary energy is still very low, standing at 0.5% according to [4]. Generally, increasing RES integration and reducing heavy dependence on fossil fuels for energy production has been at the forefront of the goals set by several countries, resulting in a significant increase of RES in the recent years [5]. This urgency comes mainly from the need to reduce greenhouse gases, a large portion of which comes from conventional energy sources [6]. In the long term, the energy production share of RESs is expected to increase between 30 to 80% by 2100 [7]. Such wide range estimation comes from the present uncertainty surrounding the efforts of decommissioning nuclear power plants. In this regard, only a few countries such as Germany have so far shown determination to scale down or even permanently abolish using nuclear sources for energy production [8].

The transition from conventional to "clean" energy power generation paradigm involves a significant number of social, economic, environmental, political and technological factors [9]. With these changes, the creation of a standard set for renewable and environmental policies, which lead to the direct creation of a new chain of value, is required. The development of such strategies will cause geopolitical changes in the energy area [10].

Among the vast non-conventional generation sources, solar and wind power sources have been especially attracting large-scale investments in recent years. In particular, the level of RES-based distribution generation (DG) has been steadily increasing in many electrical distribution systems. However, the integration of RESs has certain challenges [11]. The most prominent challenge emanates from the nature of such resources. These resources are subject to natural variation and partial unpredictability (uncertainty), both of which make the operation, control and planning of power systems very complicated. In addition, the integration of RESs (if not properly planned and managed) may pose technical challenges such as uncertain current flows and voltage violations, network congestion and increasing losses among others. These challenges are especially critical at distribution levels as the reliability, power quality and system stability could be undermined. To overcome or alleviate the negative consequences of RES integration in the distribution systems, a number of smart-grid related technologies and concepts are available which can be rolled out in coordination with the variable energy sources. Among these technologies, energy storage systems (ESSs) have been poised to be viable solutions to increase the level of penetration of RES-based distributed generations while minimizing their side effects [12]. The use of ESS “levels” the gap between renewable generation and demand by storing energy in periods of low electricity demand or high production from renewable energy sources, and releasing the stored energy in periods of higher demand [13]. Such a practice brings about several technical and economic benefits especially in terms of cost reduction as well as reliability, power quality and stability improvements in the system. In addition, distribution reconfiguration can increase the flexibility of the network system, possibly paving the way to an increased penetration level of variable energy sources.

Given the background, this paper develops a new joint optimization model that maximizes the RES integration in distribution network systems. The model simultaneously determines the optimal allocation, sizing and timing of DGs as well as ESSs. In addition, this work presents a comprehensive analysis on the impacts of distribution reconfiguration and joint deployment of ESSs on the RES-based integration level.

1.2. Literature Review

This section presents a detailed review of relevant works in the subject areas of distribution network reconfiguration, distributed generation and energy storage systems from the perspective of maximizing renewable DG integration. The ultimate goal for the simultaneous consideration of distribution system reconfiguration (DSR) and ESS and DG deployments is to support a large-scale RES integration.

The increased penetration of variable renewable DGs will have a positive and/or negative impact based on system conditions. Conventional electrical networks carry a unidirectional power flow. The introduction of DGs implies a bidirectional power flow, and increased variability and uncertainty in the system. Such variability and uncertainty of RES power production can be partly counterbalanced by deploying ESSs. In other words, integrating ESSs in the network systems can counteract the unpredictable variation of the energy supplied by intermittent RESs. In addition, ESSs balance demand and power generation. Excess energy is stored during periods of high RES power production and low demand, and is released during periods of peak demand [13]. The placement and sizing optimization of ESSs is important to mitigate the unpredictable variation of the energy supplied by RESs. In [14], authors present a detailed review on this subject area, including the individual ESS applications with respect to several storage options, settings, sizing methodologies and control.

Previous studies in the literature about DSR has traditionally focused on the minimization of system losses [15]. However, the DSR problem needs to address not only the classic objectives, i.e. minimizing losses, the voltage profile improvement and/or system reliability, but also two additional problems complementary to these issues: the massive RES integration and the paradigm of smart grid from the perspective of intelligent reconfiguration [16], [17], [18]. Because of all this, performing reconfiguration is becoming one of the most relevant topics in connection with the distribution network systems.

Based on the solution techniques applied to solve the problem pertaining to the simultaneous integration DGs and ESSs along with DSR, the literature can be broadly categorized as: (i) heuristic and metaheuristic techniques [19], [20]; (ii) mathematical techniques [21]–[23]; (iii) hybrid techniques [24], [25].

A number of heuristic and metaheuristic techniques have been employed in the literature. Ref. [26] uses particle swarm optimization (PSO) to find the optimal location and sizing of ESSs with the aim of reliability improvement in radial electrical distribution networks. The proposed optimal ESS planning is addressed as an optimization problem which aims at minimizing the cost of energy not supplied (ENS) as well as installation costs of ESSs while respecting a number of technical constraints. These include security constraints such as voltage and line flow limits. Authors in [27] propose a method to find the energy and power capacities of a storage system that minimizes the operating cost of a microgrid system. The energy management strategy

(EMS) used is based on a fuzzy expert system which is responsible for setting the power output of the ESS. The design of the energy management strategy is carried out by means of a genetic algorithm, which is used to set the fuzzy rules and membership functions of the expert system. Since the size of storage system has a major influence on the energy management strategy, ESSs are jointly optimized with EMS. In addition, the proposed method uses an aging model to predict the lifetime of ESSs. Authors in [28] present a methodology for the optimal allocation and economic analysis of ESS in microgrids on the basis of a net present value (NPV). As the performance of a microgrid strongly depends on the allocation and arrangement of its ESS, optimal allocation methods and economic operation strategies of ESSs are required for the microgrid. A matrix real-coded genetic algorithm is applied to find an optimal ESS allocation, in which each chromosome in the algorithm consists of a 2-D real number matrix representing the generation schedule of ESSs and distributed generation sources.

The literature also includes some works based on mathematical techniques. Authors in [29] suggest a dynamic programing approach to compute the optimal energy management of storage devices in grid-connected microgrids. Stored energy is controlled to balance the power of loads and renewable sources, in effect minimizing the overall cost of energy. The algorithm incorporates an arbitrary network topology, which can be a general one-phase, balanced, or unbalanced three-phase system. It employs a power flow solver in network domain, within a dynamic programming recursive search in time domain. In [30], authors have modelled the impact of real-time pricing schemes (from the smart grids perspective) on a hybrid DG system (mixed generation for heating and electricity loads) coupled with storage units. They have formulated a dynamic optimization model to represent a real-life urban community's energy system composed of a co-generation unit, gas boilers, electrical heaters and a wind turbine. Ref. [31] calculates electricity grid losses while considering limitations of using energy storage devices. Dynamic programming is used to solve the problem on CIGRÉ low voltage grid as a standard benchmark. Authors in [32] analyse the technical and economic impacts of distributed generators along with energy storage devices on distribution systems. The technical analysis includes analysing the transient stability of a system with DGs and energy storage devices such as battery and ultracapacitor. DGs are represented as small synchronous and induction generators. Different types and locations of faults and different penetration levels of DGs are considered in the analysis. For economic analysis, the costs of the system with different DG technologies and energy storage devices are compared using the software tool "hybrid optimization model for electric renewables (HOMER)". In [23], the proposed model aims to minimize the total NPV cost (investment, maintenance, losses and unserved energy). As already mentioned earlier, most of the previous works install a given amount of RESs at predetermined locations in the network. In [33], authors propose an optimal contingency assessment model using a two-stage stochastic linear programming including wind power generation and a generic ESS. The optimization model is applied to find the best radial topology by determining the best switching sequence considering contingencies. Another perspective is through the smart grids paradigm. In the smart grid context, hourly reconfiguration is still under-researched idea, but this may partly help to solve the problem of RES fluctuations. Authors in [22] explore the potential of increasing DG integration in distribution systems both in a static (reconfiguration in each planning stage) or dynamic network topology (reconfiguration using remotely controlled switches and network management schemes).

The literature in the hybrid methods category is summarized as follows. Authors in [34] propose two different strategies for constructing reliable microgrids considering temporary and sustained faults, and supply-adequate microgrids considering both real and reactive power self-sufficiency. This is defined as a new probabilistic index for simultaneous consideration of reliability indices, real and reactive supply-adequacy for the construction of microgrids. All this take into account the uncertainty in the characteristics of the DG units and loads for constructing and enhancing microgrids. For the sensitivity studies, two corrective actions are proposed to improve the performance of microgrids in terms of reliability and supply-adequacy. Three different types of algorithms are used at different stages, including a tabu search optimization algorithm as the main optimization method and graph theory-related algorithms as well as forward–backward-based probabilistic power flow methods.

As mentioned earlier, there is a global consensus for the integration of DG sources, especially RES as a way to meet the growing demand for electric energy and to reduce the carbon footprint of energy production. Nevertheless, the realization of this considerable objective faces two big challenges. The first challenge is related to the variability and uncertainty introduced on the system by RESs. The second one is related to the stability of the system and quality of energy supplied. To overcome these challenges, it is necessary to integrate a set of enabling technologies, as well as design an effective coordination mechanism among different technologies in distribution systems. It should be noted that, in addition to these challenges, there exists a set of system restrictions related to operation as well as economics that cannot be violated. The integration of these technologies is a topic which has been researched for some time; yet, integration of a specific set, namely DG and ESS along with dynamic DSR has not been adequately studied. Therefore, the main contribution of the present work lies in the joint analysis of these technologies with the specific aims of improving system flexibility, increasing RES penetration, reducing losses, enhancing system stability and reliability.

1.3. Contributions

The main contributions of this work are twofold:

- A multi-stage and stochastic optimization model, which considers simultaneous integration of ESSs and RES based DGS as well as network reconfiguration/investments;
- A thorough analysis related to the impacts of system flexibility as a result of network reconfiguration and expansion, and/or ESS deployments made in coordination with investments in variable generation sources on the RES integration level, system cost and losses.

1.4. Structure

The remainder of this paper is organized as follows. Section 2 presents a brief description of the developed mathematical model. Numerical results are discussed in Section 3. The last section concludes this paper.

2. Model Formulation

2.1 Description of Terminologies

Some terminologies used in this paper are snapshot, scenario and time stage. A snapshot refers to an hourly operational situation. Alternatively, it can be understood as a demand—generation pattern at a given hour. A scenario, on the other hand, denotes the evolution of an uncertain parameter over a given time horizon (often yearly). For example, the hourly variations of wind power production and electricity consumption collectively form a group of snapshots; whereas, the annual demand growth (which is subject to uncertainty) and RES power output uncertainty are represented by a number of possible storylines (scenarios) [35]. Time stage (also referred to as decision stage) stands for the yearly decision stages throughout the planning horizon. The length of planning horizon in the present work is three years, which is divided into yearly decision stages.

2.2. Objective Function

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

The first term in (1), $TInvC$, represents the total investment cost under the assumption of a perpetual planning horizon. In other words, "the investment cost is amortized in annual instalments throughout the lifetime of the installed component".

Here, the total investment cost is the sum of investment costs of DGs, distribution network system (DNS) components (feeders and transformers) and ESSs, as in (2). This cost is computed as in (7)—(9).

The second term, TMC, in (1) denotes the total maintenance costs which is given by the sum of maintenance costs of new and existing DGs as well as that of DNS components and ESSs at each stage plus the corresponding costs incurred after the last time stage, as in (3). Note that the latter depend on the maintenance costs of the last stage according to a perpetual planning horizon. These maintenance costs are computed using Eqs. (10)—(12).

The third term, TEC, in (1) refers to the total cost of energy in the system, which is the sum of the cost of power produced by new and existing DGs, supplied by ESSs and purchased from upstream at each stage as in (4). Equation (4) also includes the total energy costs incurred after the last time stage under the assumption of a perpetual planning horizon. Note that these costs depend on the energy costs of the last stage. The detailed mathematical expressions for computing the cost of DG power produced and ESS power supplied as well as that of purchased power are given in (13), (14) and (15), respectively. The fourth term $TENSC$ represents the total cost of unserved power in the system, given as in (5). This is computed using Eq. (16). The last term, $TEmiC$, gathers the total emission costs in the system, given by the sum of emission costs for the existing and new DGs in Eqs. (17)—(19) as well that of purchased power (20).

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

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

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

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

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

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

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

Equation (2) translates the total investment costs within the planning horizon, where $InvC_t^{DG}$ denotes the investment costs of DGs, $InvC_t^{DNS}$ is the investment costs in the distribution network system and $InvC_t^{ES}$ is the investment cost in ESS. Equation (3) represents the total maintenance costs of new and existing DGs, DNS components and ESSs at each stage. These costs are updated by the NPV factor associated to each year. Here, $MntC_t^{DG}$ denotes the maintenance cost of DGs while $MntC_t^{DNS}$ and $MntC_t^{ES}$correspond to the maintenance costs of distribution network system and ESSs, respectively. Equation (4) shows the total cost of energy in the system, which is the sum of the cost of power produced by new and existing DGs, supplied by ESSs and purchased from upstream at each stage. $TENSC$ in (5) represents the total cost of unserved power in the system. This is interpreted as the energy not supplied costs ($ENSC$). The total emission cost of power production using DGs ($EmiC_t^{DG}$) and that of purchased power ($EmiC_t^{SS}$) is given by (6).

Equations (7)—(9) represent the investment costs of DGs, feeders and energy storage system, respectively. Notice that all investment costs are weighted by the capital recovery factor, $\frac{r(1+r)^{LT}}{(1+r)^{LT}-1}$. The formulations in (7)—(10) ensure that the investment cost of each component added to the system is considered only once in the summation.

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

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

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

Equation (10) stands for the maintenance costs of new and existing DGs at each time stage. The maintenance cost of a new/existing feeder is included only when its corresponding investment/utilization variable is different from zero, as shown in (11). Equation (12) is related to the maintenance costs of energy storage at each stage.

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

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

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

The total cost of power produced by new and existing DGs is given by equation (13). Note that these costs depend on the amount of power generated in each scenario, snapshot and stage. Therefore, they represent the expected costs of operation. Similarly, equations (14) and (15) account for the expected costs of energy supplied by the energy storage system, and that purchased from upstream (i.e. transmission grid), respectively.

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

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

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

The penalty for the unserved power, given by (16), is also dependent on the scenarios, snapshots and time stages. Therefore, Equation (16) gives the expected cost of unserved energy in the system.

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

The expected emission costs of power generated by new and existing DGs are given by (17)—(19), and that of energy purchased from the grid is calculated using (20). Note that, for the sake of simplicity, a linear emission cost function is assumed here. In reality, the emission cost function is highly nonlinear and nonconvex, as in [36].

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

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

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

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

Note that ρ_s denotes the probability of each scenario while π_w is the weight associated with each representative snapshot. These parameters appear in Eqs. (13)—(20). Setting values for these parameters is not generally straightforward. For the sake of simplicity, all scenarios are assumed to be equally probable. The steps being followed to determine the value of each representative snapshot are described as follows. First, a large number of snapshots are clustered into a predefined number of groups, substantially lower than the original number of snapshots. The number of groups needs to ideally strike the right balance between accuracy and numerical feasibility. Each group contains a set of snapshots with similar characteristics. Then, a representative snapshot (for instance, the medoid) is selected in each group. This snapshot is used in the analysis by assigning a weight π_w proportional to the number of snapshots grouped together.

2.3. Constraints

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

The active power balance at each node is enforced by equation (21):

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

Equation (21) denotes that the sum of all incoming flows should be equal to the sum of all outgoing flows at each node. The losses in every feeder are considered as "virtual loads" which are equally distributed between the nodes connecting the feeder. Note that losses are a quadratic function of flows (not shown here). Hence, they are linearized using a first order approximation, as in [23]. Five linear partitions are used throughout the analysis in this paper, which is in line with the findings in [37].

b) Energy Storage Model Constraints

For the sake of simplicity, a generic ESS is employed here. This is modelled by the set of constraints in (22)—(28). Equations (22) and (23) represent the bounds of power capacity of the ESS while being charged and discharged, respectively. Inequality (24) prevents simultaneous charging and discharging operation of the ESS in a given operational time w. The amount of stored energy in the ESS reservoir at a given operational time w as a function of the energy stored until $w-1$ is given by (25). The maximum and minimum levels of storages in the operational time w are also considered through inequality (26). Equation (27) shows the initial level of stored energy in the ESS as a function of its maximum reservoir capacity. In a multi-stage planning approach, Equation (28) ensures that the initial level of energy in the ESS at a given year is equal to the final level of energy in the ESS in the preceding year. Moreover, the reservoir level at the end of the planning horizon should be equal to the initial level, which is enforced by the second constraint in (28). Such a constraint guarantees that the optimal solution returned by the solution algorithm is not because of the initial reservoir level. Here, η^{dch}_{es} is assumed to be η^{ch}_{es}.

$$0\leq P^{ch}_{es,i,s,w,t}\leq I^{ch}_{es,i,s,w,t}x_{es,i,t}P^{ch,max}_{es,i} \quad (22)$$

$$0 \leq P^{dch}_{es,i,s,w,t} \leq I^{ch}_{es,i,s,w,t} x_{es,i,t} P^{ch,max}_{es,i} \tag{23}$$

$$I^{ch}_{es,i,s,w,t} + I^{dch}_{es,i,s,w,t} \leq 1 \tag{24}$$

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

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

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

$$E_{es,i,s,w_1,t+1} = E_{es,i,s,W,t}; \quad E_{es,i,s,W,T} = E_{es,i,s,w_0,T1} \tag{28}$$

Notice that inequalities (22) and (23) involve products of charging/discharging indicator variables and investment variable. In order to overcome these nonlinearities, new continuous positive variables $z^{ch}_{es,i,s,w,t}$, and $z^{dch}_{es,i,s,w,t}$, which replace the bilinear products in each constraint, are introduced such that the set of linear constraints in (29) and (30) hold. For instance, the product $I^{dch}_{es,i,s,w,t} x_{es,i,t}$ is replaced by the positive variable $z^{dch}_{es,i,s,w,t}$. Then, the bilinear product is decoupled by introducing the set of constraints in (29) [38]. Similarly, the product $I^{ch}_{es,i,s,w,t} x_{es,i,t}$ is decoupled by including the set of constraints in (30).

$$z^{dch}_{es,i,s,w,t} \leq x^{max}_{es} I^{dch}_{es,i,s,w,t} \;\; ; \;\; z^{dch}_{es,i,s,w,t} \leq x_{es,i,t} \;\; ; z^{dch}_{es,i,s,w,t} \geq x_{es,i,t} - \left(1 - I^{dch}_{es,i,s,w,t}\right) x^{max}_{es} \tag{29}$$

$$z^{ch}_{es,i,s,w,t} \leq x^{max}_{es} I^{ch}_{es,i,s,w,t} \;\; ; \;\; z^{ch}_{es,i,s,w,t} \leq x_{es,i,t} \;\; ; z^{ch}_{es,i,s,w,t} \geq x_{es,i,t} - \left(1 - I^{ch}_{es,i,s,w,t}\right) x^{max}_{es} \tag{30}$$

c) Active Power Limits of DGs

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

$$P_{g,i,s,w,t}^{E,min} u_{g,i,t} \leq P_{g,i,s,w,t}^{E} \leq P_{g,i,s,w,t}^{E,max} u_{g,i,t} \quad (31)$$

$$P_{g,i,s,w,t}^{N,min} x_{g,i,t} \leq P_{g,i,s,w,t}^{N} \leq P_{g,i,s,w,t}^{N,max} x_{g,i,t} \quad (32)$$

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

d) Active Power Limits of Power Purchased

$$P_{s,w,t}^{SS,min} \leq P_{s,w,t}^{SS} \leq P_{s,w,t}^{SS,max} \quad (33)$$

For technical reasons, the power that can be purchased from the transmission grid could have minimum and maximum limits, which is enforced by (33). However, it is understood that setting such limits is difficult. These constraints are included here for the sake of completeness. In this work, these limits are set to 1.5 times the minimum and maximum levels of the total load in the system.

e) Logical constraints

The set of logical constraints in (34) ensure that an investment decision already made cannot be reversed. In addition to the constraints described above, the direct current (DC) based network model and radiality related constraints presented in [23] are used here.

$$x_{k,t} \geq x_{k,t-1}; \quad x_{g,i,t} \geq x_{g,i,t-1}; \quad x_{es,i,t} \geq x_{es,i,t-1} \quad (34)$$

f) Radiality constraints

There are two conditions that must be fulfilled in order a distribution network system (DNS) to be radial. First, the solution must have $N_i - N_{SS}$ circuits. Second, the final topology should be connected. Equation (35) represents the first necessary condition for maintaining the radial topology of a DNS.

$$\sum_{k\in\Omega^{ij}} OR(x_{k,t}, u_{k,t}) = N_i - N_{SS} \qquad ;\forall t \tag{35}$$

Note that the above equation assumes that a line investment is possible in all corridors. Hence, in a given corridor, we can have either an existing branch or a new one, or both connected in parallel, depending on the economic benefits of the final setup (solution) brings about to the system. The radiality constraint in (35) then has to accommodate this condition. One way to do this is using the Boolean logic operation given as in (35). Unfortunately, this introduces nonlinearity. We show how this logic can be linearized using an additional auxiliary variable $z_{k,t}$ and the binary variables associated to existing and new branches i.e. $u_{k,t}$ and $x_{k,t}$, respectively. Given$z_{k,t} := OR(x_{k,t}\ ,\ u_{k,t})$, this Boolean operation can be expressed using the following set of linear constraints:

$$z_{k,t} \leq x_{k,t} + u_{k,t};\quad z_{k,t} \geq x_{k,t};\quad z_{k,t} \geq u_{k,t}; 0 \leq z_{k,t} \leq 1 \qquad ;\forall t \tag{36}$$

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

$$\sum_{k\in\Omega^{ij}} z_{k,t} = N_i - N_{SS} \qquad ;\forall t \tag{37}$$

When all loads in the DNS are only powered up by power imported through a number of substations, the final solution obtained automatically satisfies the two aforementioned conditions; hence, no additional constraints are required i.e. (36) along with (37) are sufficient to guarantee radiality. However, it should be noted that, in the presence of DGs and reactive power sources, these constraints alone may not ensure the radiality of the distribution network, as pointed out in [39] and further discussed in [40].

3. Numerical Results and Discussions

3.1. Data and Assumptions

The standard IEEE 119-bus distribution network, shown in Figure 1, is used here for carrying out the required analysis mentioned earlier. The system has a rated voltage of 11.0 kV, and a total demand of 22709.72 kW and 17041.068 kVAr. Network data and other related information about this test system can be found in

[41]. According to [42], the active power losses in this system is 1298.09 kW, and the minimum node voltage of the system is 0.8783 p.u., which occurs at bus 116.

"Figure 1"

Other data and assumptions made throughout this paper are as follows. The planning horizon is 3 years long, which is divided into yearly decision stages, and a fixed interest rate of 7% is used. The expected lifetime of the generic ESS is assumed to be 15 years while that of DGs and feeders is 25 years. Two investment options with installed capacities of 0.5 and 1.0 MVA are considered for each wind and solar PV type DG units. The installation cost and emission related data of these DG units in [43] are used here. For the sake of simplicity, all maintenance cost of each DG is assumed to be 2% of the corresponding investment cost while that of any feeder is 450 €/km/year. The investment cost of each feeder is 38700 €/km. The current flow limits of each feeder are considered to be as follows. The current limit in each of the feeders {(1,2); (2,4); (1,66); (66,67)} is 1200 A while the set of feeders {(4,5); (5,6); (6,7); (4,29); (29,30); (30,31); (67,68); (67,81); (81,82); (1,105); (105,106); (106,107)} have each 800 A capacity limit. The current flow limits of the remaining feeders are considered to be 400 A. Moreover, it is assumed that all feeders can be switched on/off, if deemed necessary.

In addition, it is assumed that the availability of wind and solar power sources is uniform throughout the system nodes. The operational variability and uncertainty introduced by wind and solar PV type DGs, demand and electricity price are accounted for via the clustering method proposed in [44]. The maximum allowable bus voltage deviation in the system is set to 5%, and node 1 is considered as a reference with a voltage magnitude of 1.0. Taking the base case demand as a reference, annual demand growths of 0%, 5% and 10% are also considered in all simulations. Emission prices in the first, second and third time stages are set to 25, 45 and 60 €/tCO2e, respectively, and the emission rate of power purchased from upstream is arbitrarily set to 0.4 tCO2e/MWh. The cost of unserved energy is 2000 €/MWh. A power factor of 0.9 is considered throughout the system, and is assumed to be the same throughout. The base power is set to 1 MVA. An ESS with a 1 MW power and a 5 MWh reservoir capacity is considered for investment.

3.2. Discussion of Numerical Results

Given the aforementioned data and assumptions, the developed optimization problem has been solved considering six different cases (designated as A through F). Case A represents the base case topology where no investments are made. This case can be alternatively understood as the “do-nothing” scenario. Case B is similar to the base case (i.e. with no investments) but considers the network reconfiguration problem. Case C corresponds to a scenario where only DG investments are made on the base case topology (i.e. without reconfiguration). Case D is similar to Case C except that the former simultaneously considers optimal reconfiguration and DG investments. The last two cases (Cases E and F) correspond to scenarios where optimal investment planning in DGs is coordinated with that of ESSs. The difference is that Case E uses the base case topology (i.e. without reconfiguration) while Case F optimizes the network via reconfiguration. Table 1 clearly summarizes the different cases.

"Table 1"

The values of the most relevant variables are analysed (as depicted in Table 2) over the three years planning horizon. The results in Table 2 reveal the significant differences in overall NPV cost in the system, share of the combined energy supplied by RES and ESS, cost of total network losses and unserved power among the aforementioned cases. The results are also compared with the base case system where no investments are made and the network topology is held the same (i.e. the "do-nothing" scenario). Carrying out an optimal reconfiguration of the network alone, as in Case B, results in about 5.44 % reduction in the cost of losses, and a 15.9% reduction in the NPV overall system cost compared with that of Case A.

In addition, network reconfiguration reduces a total of 1.18 p.u. average load curtailment in the third year to 0.57 p.u. in Case B that would otherwise occur at nodes 52, 53, 54, 55, 56 and 116 due to a number of factors such as technical constraints and high demand level.

Another more interesting observation from Table 2 is that Cases C and D lead to (approximately) 50% reduction in the overall system cost, and a 75% reduction in the amount of imported energy. Wind and solar power sources are complementary by nature. This natural phenomenon seems to be exploited when DG investments are not accompanied by investments in ESSs (i.e. Cases C and D). This is because, according to the DG investment solution in Table 2, the operational variability in the system seems to be handled by investing an appreciable amount in both complementary power sources (wind and solar). The level of demand covered by RESs in both cases amounts to nearly 75%. Moreover, as a result of investing in DGs, losses in the system are slashed down by about 82%. Generally, the corresponding reductions in Case D are slightly higher than those in Case C. This is due to the network reconfiguration which has been considered in Case D.

"Table 2 ".

The results corresponding to Cases E and F show that the total cost and cost of losses are dramatically reduced by more than 60% and 90%, respectively. These figures are in line with the results reported in a similar work [18]. The reductions in active losses are 88.56% and 89.66%, respectively. Moreover, the amount of imported energy is 11% and 10% of the total energy demand in Cases E and F, respectively. All this reveals the substantial benefits of coordinating investments in DG with ESSs. Generally, ESSs significantly improve system flexibility, enabling large-scale accommodation of RES energy. Interestingly, the total amount of installed DGs (40 MVA) is lower in Cases E and F (with ESSs) than in Cases C and D (without ESSs). Even if this is the case, in the absence of a storage medium (as in Cases C and D), there may be frequent RES power spillages when the demand is lower than the total generated power. However, the installation of ESSs leads to an efficient utilization of RES power. This is evident from the amount of energy consumption covered by the combined energy from RESs and ESSs in Cases E and F is about 90%. Normally, a network switching capability also improves system flexibility, leading to a high level RES penetration. In this particular study, the effect of network switching on the level of RES power absorbed by the system is not significant as one can observe in Table 2. This may however be case-dependent. A more frequent switching capability could, for instance, have a significant impact.

The optimal location and size of installed DGs and ESSs corresponding to Cases C through F is summarized in Table 3. This is also conveniently plotted in Figure 2. As the formulated problem is based on a multi-year decision framework, the aggregate investment decisions made in each stage along the planning horizon is presented in Table 4. As it can be seen in this table, majority of the investments are made in the first stage. This may be because of two reasons. The first one could be due to lack of appropriate financial and logistical constraints in the optimization model. The second and most plausible reason could be due to higher NPV factor of the first stage than any subsequent one. Note that the higher this factor is, the more relevant the associated costs in the objective function are, hence, leading to more investments in DGs and ESSs.

"Table 3 ".

"Figure 2 ".

"Table 4 ".

"Figure 3 ".

"Figure 4 ".

The average voltage profiles at each node and for each case are depicted in Figure 3. A cumulative distribution of the average voltage values, corresponding to different cases, is also conveniently represented in Figure 4. In both figures, it is interesting to see the substantial contributions of DG and ESS installations to voltage profile improvement. As shown in Figure 3, the coordinated integration of DGs and ESSs along with reconfiguration (i.e. Case F), especially leads to the best voltage profile which is almost flat throughout the system.

"Table 5 ".

Table 5 compares the optimal network topologies (i.e. the switches to be opened) corresponding to the different cases with that of the base case topology. The benefit of joint DG and ESS investments along with network reconfiguration in terms of losses reduction (over 89% on average) can be seen in Figure 5. The spikes observed in cases D and F are because of the variability in the RES power injected into the system.

"Figure 5 ".

As stated earlier, stability concern is one of the major issues that are associated with high level RES integration in distribution systems. The controllability of voltage and frequency can be dramatically undermined or even sometimes become out of reach. Because of these reasons, the penetration level of DGs (including RESs) in many distribution systems is limited to a value often less than about 25%. However, this contradicts with the ambition to meet other objectives such as reducing the carbon footprint of power production and ensuring energy security among others. The integration of RESs is likely to be supported with enabling technologies that have the capability to effectively address the integration challenges and consequently increase the penetration level. The numerical results in this work largely demonstrate the fact that large-scale integration of variable energy sources is possible when such energy sources are optimally deployed with ESSs and a mechanism that improve the flexibility of the network is put in place.

4. Conclusions

This paper has investigated the impacts of installing ESSs as well as network switching on the level of renewable power integration in a distribution network system. A stochastic MILP optimization model has been developed for this purpose. The resulting model is equipped with the necessary tools to jointly optimize the placement, timing and sizing of RES-based DGs and ESSs in coordination with optimal network reconfiguration while respecting a number of technical, economic and environmental constraints. Numerical results have showed the capability of ESS integration in dramatically increasing the level and the optimal exploitation of renewable DGs. According to the simulation results, the simultaneous integration of DGs and ESSs resulted in an overall cost and average losses reduction of 60% and 90%, respectively. Moreover, as high as 90% RES penetration level seems to be largely possible provided that this is supported by ESS deployments. The optimal network reconfiguration, DG and ESS installations (jointly or separately) substantially contributed to voltage stability. In this particular case study, the impact of network switching on RES power integration has not been significant. However, it should be noted that this can be case-dependent; a more frequent switching operation can substantially influence the level of renewable integration.

Acknowledgments

This work was supported by FEDER funds through COMPETE 2020 and by Portuguese funds through FCT, under Projects FCOMP-01-0124-FEDER-020282 (Ref. PTDC/EEA-EEL/118519/2010), POCI-01-0145-FEDER-006961, UID/EEA/50014/2013, UID/CEC/50021/2013, and UID/EMS/00151/2013. Also, the research leading to these results has received funding from the EU Seventh Framework Programme FP7/2007-2013 under grant agreement no. 309048. Moreover, Sérgio Santos gratefully acknowledges the UBI / Santander Totta doctoral incentive grant in the Engineering Faculty.

References

[1] J. Yan, T. Shamim, S. K. Chou, U. Desideri, and H. Li, "Clean, efficient and affordable energy for a sustainable future," *Appl. Energy*, Jun. 2016.

[2] *Renewables 2015 - Global Status Report*, Renewable Energy Policy Network for the 21st Century. .

[3] A. Aslani, P. Helo, and M. Naaranoja, "Role of renewable energy policies in energy dependency in Finland: System dynamics approach," *Appl. Energy*, vol. 113, pp. 758–765, Jan. 2014.

[4] Y. Wang, S. Zhou, and H. Huo, "Cost and CO2 reductions of solar photovoltaic power generation in China: Perspectives for 2020," *Renew. Sustain. Energy Rev.*, vol. 39, pp. 370–380, Nov. 2014.

[5] V. Krakowski, E. Assoumou, V. Mazauric, and N. Maïzi, “Feasible path toward 40–100% renewable energy shares for power supply in France by 2050: A prospective analysis,” *Appl. Energy*, vol. 171, pp. 501–522, Jun. 2016.

[6] M. Bhattacharya, S. R. Paramati, I. Ozturk, and S. Bhattacharya, “The effect of renewable energy consumption on economic growth: Evidence from top 38 countries,” *Appl. Energy*, vol. 162, pp. 733–741, Jan. 2016.

[7] G. Gutiérrez-Alcaraz, E. Galván, N. González-Cabrera, and M. S. Javadi, “Renewable energy resources short-term scheduling and dynamic network reconfiguration for sustainable energy consumption,” *Renew. Sustain. Energy Rev.*, vol. 52, pp. 256–264, Dec. 2015.

[8] F. Hedenus, C. Azar, and D. J. A. Johansson, “Energy security policies in EU-25—The expected cost of oil supply disruptions,” *Energy Policy*, vol. 38, no. 3, pp. 1241–1250, Mar. 2010.

[9] A. Colmenar-Santos, C. Reino-Rio, D. Borge-Diez, and E. Collado-Fernández, “Distributed generation: A review of factors that can contribute most to achieve a scenario of DG units embedded in the new distribution networks,” *Renew. Sustain. Energy Rev.*, vol. 59, pp. 1130–1148, Jun. 2016.

[10] B. Fais, M. Blesl, U. Fahl, and A. Voß, “Comparing different support schemes for renewable electricity in the scope of an energy systems analysis,” *Appl. Energy*, vol. 131, pp. 479–489, Oct. 2014.

[11] P. S. Georgilakis and N. D. Hatziargyriou, “Optimal Distributed Generation Placement in Power Distribution Networks: Models, Methods, and Future Research,” *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 3420–3428, Aug. 2013.

[12] A. Chauhan and R. P. Saini, “A review on Integrated Renewable Energy System based power generation for stand-alone applications: Configurations, storage options, sizing methodologies and control,” *Renew. Sustain. Energy Rev.*, vol. 38, pp. 99–120, Oct. 2014.

[13] M. Aneke and M. Wang, “Energy storage technologies and real life applications – A state of the art review,” *Appl. Energy*, vol. 179, pp. 350–377, Oct. 2016.

[14] A. Chauhan and R. P. Saini, “A review on Integrated Renewable Energy System based power generation for stand-alone applications: Configurations, storage options, sizing methodologies and control,” *Renew. Sustain. Energy Rev.*, vol. 38, pp. 99–120, Oct. 2014.

[15] D. Q. Hung and N. Mithulananthan, “Loss reduction and loadability enhancement with DG: A dual-index analytical approach,” *Appl. Energy*, vol. 115, pp. 233–241, Feb. 2014.

[16] M. R. Dorostkar-Ghamsari, M. Fotuhi-Firuzabad, M. Lehtonen, and A. Safdarian, “Value of Distribution Network Reconfiguration in Presence of Renewable Energy Resources,” *IEEE Trans. Power Syst.*, vol. 31, no. 3, pp. 1879–1888, May 2016.

[17] I.-K. Song, W.-W. Jung, J.-Y. Kim, S.-Y. Yun, J.-H. Choi, and S.-J. Ahn, “Operation Schemes of Smart Distribution Networks With Distributed Energy Resources for Loss Reduction and Service Restoration,” *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 367–374, Mar. 2013.

[18] D. Q. Hung, N. Mithulananthan, and R. C. Bansal, “A combined practical approach for distribution system loss reduction,” *Int. J. Ambient Energy*, vol. 36, no. 3, pp. 123–131, May 2015.

[19] Y.-K. Wu, C.-Y. Lee, L.-C. Liu, and S.-H. Tsai, “Study of Reconfiguration for the Distribution System With Distributed Generators,” *IEEE Trans. Power Deliv.*, vol. 25, no. 3, pp. 1678–1685, Jul. 2010.

[20] F. S. Abu-Mouti and M. E. El-Hawary, “Optimal Distributed Generation Allocation and Sizing in Distribution Systems via Artificial Bee Colony Algorithm,” *IEEE Trans. Power Deliv.*, vol. 26, no. 4, pp. 2090–2101, Oct. 2011.

[21] D. Q. Hung, N. Mithulananthan, and R. C. Bansal, “An optimal investment planning framework for multiple distributed generation units in industrial distribution systems,” *Appl. Energy*, vol. 124, pp. 62–72, Jul. 2014.

[22] F. Capitanescu, L. F. Ochoa, H. Margossian, and N. D. Hatziargyriou, “Assessing the Potential of Network Reconfiguration to Improve Distributed Generation Hosting Capacity in Active Distribution Systems,” *IEEE Trans. Power Syst.*, vol. 30, no. 1, pp. 346–356, Jan. 2015.

[23] G. Munoz-Delgado, J. Contreras, and J. M. Arroyo, “Joint Expansion Planning of Distributed Generation and Distribution Networks,” *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2579–2590, Sep. 2015.

[24] C. Lueken, P. M. S. Carvalho, and J. Apt, “Distribution grid reconfiguration reduces power losses and helps integrate renewables,” *Energy Policy*, vol. 48, pp. 260–273, Sep. 2012.

[25] H. R. Esmaeilian and R. Fadaeinedjad, “Energy Loss Minimization in Distribution Systems Utilizing an Enhanced Reconfiguration Method Integrating Distributed Generation,” *IEEE Syst. J.*, vol. PP, no. 99, pp. 1–10, 2014.

[26] H. Saboori, R. Hemmati, and M. A. Jirdehi, “Reliability improvement in radial electrical distribution network by optimal planning of energy storage systems,” *Energy*, vol. 93, pp. 2299–2312, Dec. 2015.

[27] J. P. Fossati, A. Galarza, A. Martín-Villate, and L. Fontán, “A method for optimal sizing energy storage systems for microgrids,” *Renew. Energy*, vol. 77, pp. 539–549, May 2015.

[28] C. Chen, S. Duan, T. Cai, B. Liu, and G. Hu, “Optimal Allocation and Economic Analysis of Energy Storage System in Microgrids,” *IEEE Trans. Power Electron.*, vol. 26, no. 10, pp. 2762–2773, Oct. 2011.

[29] Y. Levron, J. M. Guerrero, and Y. Beck, “Optimal Power Flow in Microgrids With Energy Storage,” *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 3226–3234, Aug. 2013.

[30] P. Crespo Del Granado, Z. Pang, and S. W. Wallace, “Synergy of smart grids and hybrid distributed generation on the value of energy storage,” *Appl. Energy*, vol. 170, pp. 476–488, May 2016.

[31] M. Farrokhifar, “Optimal operation of energy storage devices with RESs to improve efficiency of distribution grids; technical and economical assessment,” *Int. J. Electr. Power Energy Syst.*, vol. 74, pp. 153–161, Jan. 2016.

[32] A. K. Srivastava, A. A. Kumar, and N. N. Schulz, “Impact of Distributed Generations With Energy Storage Devices on the Electric Grid,” *IEEE Syst. J.*, vol. 6, no. 1, pp. 110–117, Mar. 2012.

[33] 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 Trans. Sustain. Energy*, vol. 6, no. 4, pp. 1524–1533, Oct. 2015.

[34] S. A. Arefifar and Y. A.-R. I. Mohamed, “DG Mix, Reactive Sources and Energy Storage Units for Optimizing Microgrid Reliability and Supply Security,” *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1835–1844, Jul. 2014.

[35] Desta Z. Fitiwi, “Strategy, Methods and Tools for Solving Long-term Transmission Expansion Planning in Large-scale Power Systems,” PhD Dissertation, Comillas Pontifical University, 2016.

[36] P. Phonrattanasak, “Optimal placement of DG using multiobjective particle swarm optimization,” in *2010 2nd International Conference on Mechanical and Electrical Technology (ICMET)*, 2010, pp. 342–346.

[37] D. Z. Fitiwi, L. Olmos, M. Rivier, F. de Cuadra, and I. J. Pérez-Arriaga, “Finding a representative network losses model for large-scale transmission expansion planning with renewable energy sources,” *Energy*, vol. 101, pp. 343–358, Apr. 2016.

[38] H. P. Williams, *Model Building in Mathematical Programming*, 4th ed. Wiley, 1999.

[39] E. Romero-Ramos, J. Riquelme-Santos, and J. Reyes, “A simpler and exact mathematical model for the computation of the minimal power losses tree,” *Electr. Power Syst. Res.*, vol. 80, no. 5, pp. 562–571, May 2010.

[40] M. Lavorato, J. F. Franco, M. J. Rider, and R. Romero, “Imposing Radiality Constraints in Distribution System Optimization Problems,” *IEEE Trans. Power Syst.*, vol. 27, no. 1, pp. 172–180, Feb. 2012.

[41] D. Zhang, Z. Fu, and L. Zhang, “An improved TS algorithm for loss-minimum reconfiguration in large-scale distribution systems,” *Electr. Power Syst. Res.*, vol. 77, no. 5–6, pp. 685–694, Apr. 2007.

[42] R. S. Rao, S. V. L. Narasimham, M. R. Raju, and A. S. Rao, “Optimal Network Reconfiguration of Large-Scale Distribution System Using Harmony Search Algorithm,” *IEEE Trans. Power Syst.*, vol. 26, no. 3, pp. 1080–1088, Aug. 2011.

[43] Z. F. Desta, A. W. Bizuayehu, M. Shafie-khah, J. P. S. Catalão, M. Asenso, and J. Contreras, “DG Investment Planning Analysis with Renewable Integration and Considering Emission Costs,” in *the 16th Int. Conf. on Computer as a Tool, EuroCon2015*, Salamanca, 2015.

[44] Gregorio Muñoz-Delgado, Sergio Montoya-Bueno, Miguel Asensio, Javier Contreras, JoséI Muñoz, and JoséM Arroyo, “Renewable Generation and Distribution Grid Expansion Planning,” in *Smart and Sustainable Power Systems*, 0 vols., CRC Press, 2015, pp. 345–404.

Figures

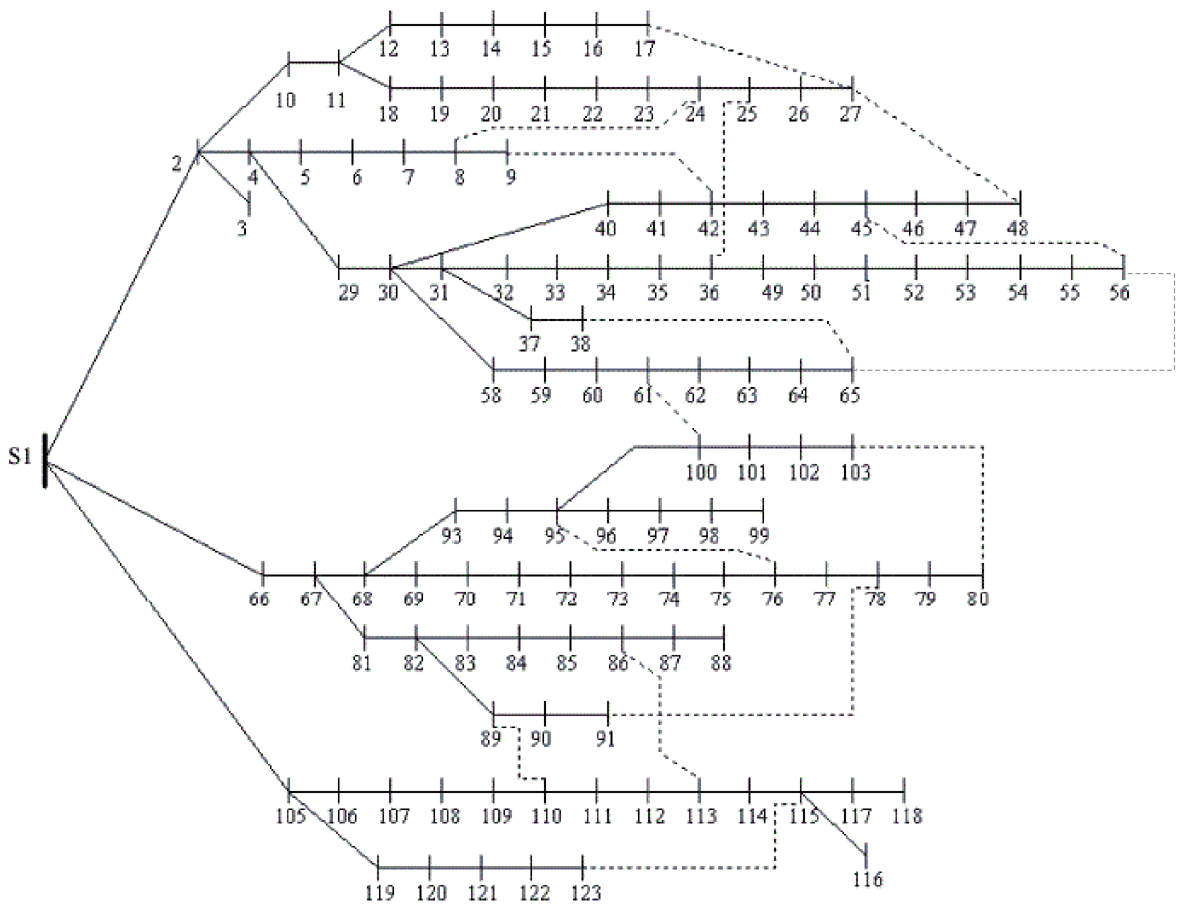

Figure 1. Single line diagram of the test system in base case.

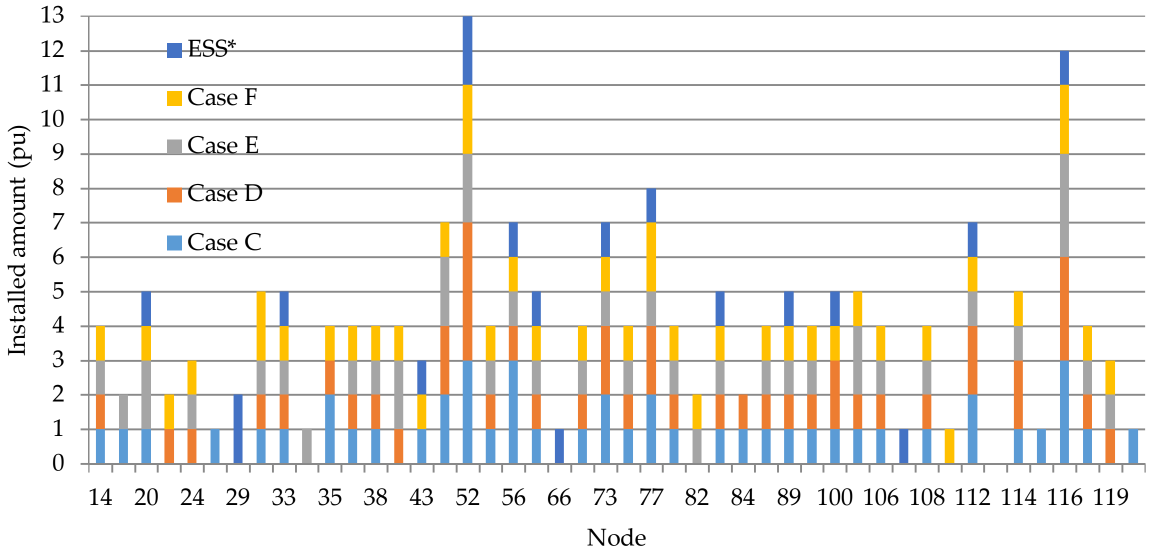

Figure 2. Optimal placement and size of DGs and ESSs for different cases (* only in cases E and F)

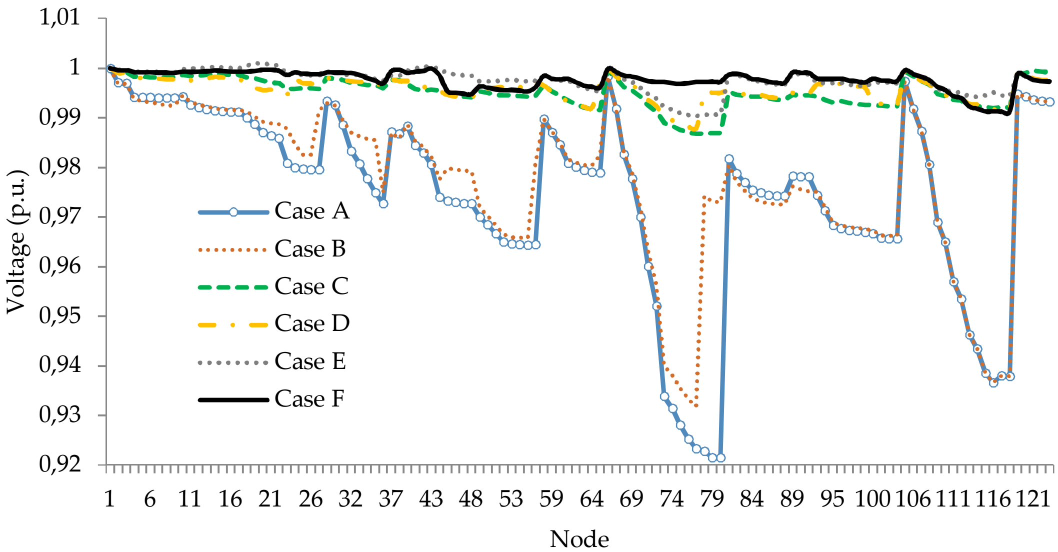

Figure 3. Average voltage profiles in the system for different cases.

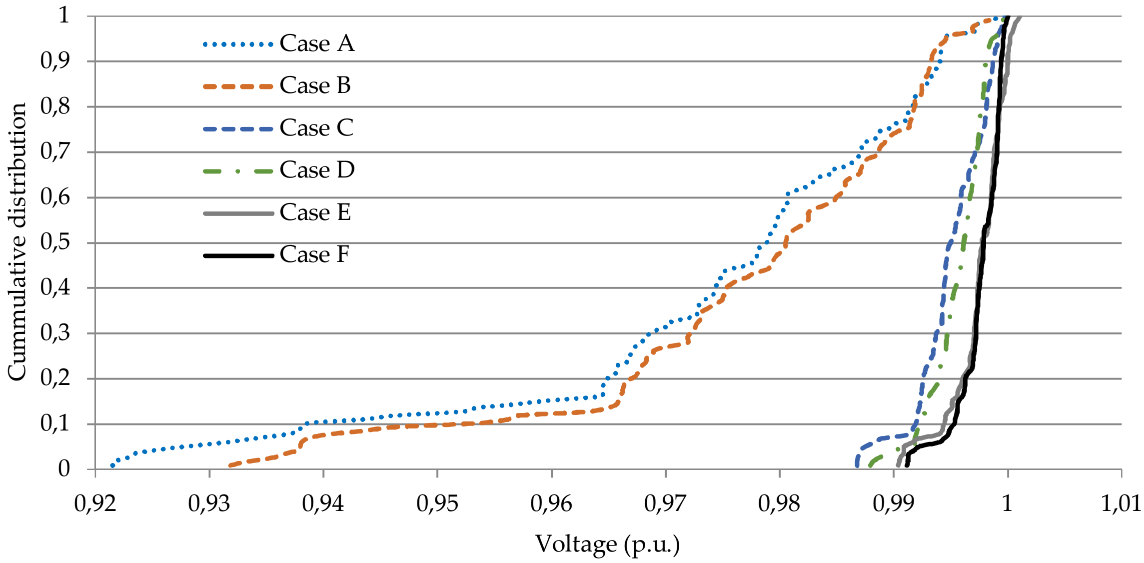

Figure 4. Cumulative distribution function of average voltages in the system for different cases.

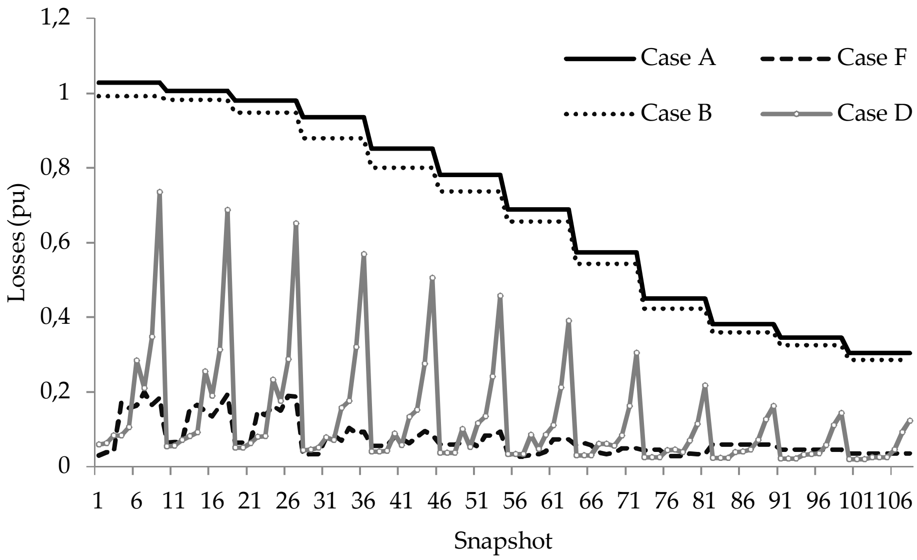

Figure 5. Total system losses profile.

Tables

Table 1. Distinguishing the different cases

Cases	Reconfiguration	Investment	
		DGs	ESSs
A	No	No	No
B	Yes	No	No
C	No	Yes	No
D	Yes	Yes	No
E	No	Yes	Yes
F	Yes	Yes	Yes

Table 2. Results of relevant variables for different cases

Optimization variables		Cases*					
		A	**B**	**C**	**D**	**E**	**F**
Cost terms (k€)	Investment	0	0	92478	88489	100754	99368
	Maintenance	189	201	52604	50355	57295	56513
	Energy + Emission	424715	433188	121820	123232	48424	48973
	PNS	94441	2095	926	0	0	0
	Losses	12515	11834	2204	2161	1242	1098
Total cost (k€)		531860	447318	270033	264236	207715	205952
Energy share (%)	Wind	-	-	64	64	89	90
	Solar	-	-	10	11	0	0
	Imported	100	100	26	25	11	10
Installed size (p.u.)	Wind	-	-	36	33	40	40
	Solar	-	-	10	11	0	0
	ESS	-	-	-	-	18	17

*A: Base case; B: Reconfiguration only; C: DG investment on base case topology; D: DG investment plus reconfiguration; E: DG and ESS investment on base case topology; F: DG and ESS investment plus reconfiguration.

Table 3. Optimal sizes and locations of DGs and ESSs for different cases

	Wind *				Solar *, §		ESS *, †	
Nodes	Case C	Case D	Case E	Case F	Case C	Case D	Case E	Case F
14	1	1	1	1	0	0	0	0
19	1	0	1	0	0	0	0	0
20	1	0	2	1	0	0	1	1
21	0	1	0	1	0	0	0	0
24	0	1	1	1	0	0	0	0
25	1	0	0	0	0	0	0	0
29	0	0	0	0	0	0	2	1
32	1	1	1	2	0	0	0	0
33	1	1	1	1	0	0	1	1
34	0	0	1	0	0	0	0	0
35	1	0	0	1	1	1	0	0
37	1	1	1	1	0	0	0	0
38	1	1	1	1	0	0	0	1
42	0	1	2	1	0	0	0	0
43	1	0	0	1	0	0	1	1
44	1	1	2	1	1	1	0	0
52	2	2	2	2	1	2	2	1
53	1	1	1	1	0	0	0	0
56	3	1	1	1	0	0	1	1
61	1	1	1	1	0	0	1	1
66	0	0	0	0	0	0	1	1
69	1	1	1	1	0	0	0	0
73	1	1	1	1	1	1	1	1
74	1	1	1	1	0	0	0	0
77	1	1	1	2	1	1	1	1
79	1	1	1	1	0	0	0	0
82	0	0	1	1	0	0	0	0
83	1	1	1	1	0	0	1	1
84	0	0	0	0	1	1	0	0
85	1	1	1	1	0	0	0	0
89	1	1	1	1	0	0	1	1
96	1	1	1	1	0	0	0	0
100	0	1	0	1	1	1	1	1
101	1	1	2	1	0	0	0	0
106	1	1	1	1	0	0	0	0
107	0	0	0	0	0	0	1	1
108	1	1	1	1	0	0	0	0
109	0	0	0	1	0	0	0	0
112	1	1	1	1	1	1	1	1
113	0	0	0	0	0	0	0	0
114	1	1	1	1	0	1	0	0
115	0	0	0	0	1	0	0	0
116	2	2	3	2	1	1	1	1
117	1	1	1	1	0	0	0	0
119	0	1	1	1	0	0	0	0
121	1	0	0	0	0	0	0	0
Total (p.u.)	34	31	38	38	10	11	18	17

*A: Base case; B: Reconfiguration only; C: DG investment on base case topology; D: DG investment plus reconfiguration; E: DG and ESS investment on base case topology; F: DG and ESS investment plus reconfiguration. § No solar type investment decisions in cases E and F; † ESS investments are not considered in the cases other than E and F.

Table 4. Optimal sizes and locations of DGs and ESSs for different cases

	Case C		**Case D**		**Case E**			**Case E**		
Year	**Wind**	**Solar**	**Wind**	**Solar**	**Wind**	**Solar**	**ESS**	**Wind**	**Solar**	**ESS**
1	31	9	29	7	36	0	17	36	0	15
2	2	0	2	2	2	0	0	1	0	2
3	3	1	2	2	2	0	1	3	0	0
Total	**36**	**10**	**33**	**11**	**40**	**0**	**18**	**40**	**0**	**17**

Table 5. Optimal reconfiguration outcome for different cases (List of switches to be opened)

Year	**Case A**	**Case B**	**Case D**	**Case F**
1	(8,24); (9,42); (17,27); (25,36); (38,65); (48,27); (56,45); (61,100); (65,56); (76,95); (91,78); (103,80); (113,86); (110,89); (115,123)	(23,24); (26,27); (35,36); (41,42); (44,45); (48,27); (54,56); (61,100); (64,65); (76,95); (77,78); (103,80); (110,89); (113,86); (115,123)	(17,27); (23,24); (35,36); (41,42); (48,27); (54,56); (56,45); (61,100); (64,65); (76,95); (77,78); (103,80); (110,89); (113,86); (115,123)	(9,42); (17,27); (23,24); (25,36); (38,65); (48,27); (54,56); (56,45); (61,100); (76,95); (91,78); (103,80); (110,89); (113,86); (115,123)
2	(8,24); (9,42); (17,27); (25,36); (38,65); (48,27); (56,45); (61,100); (65,56); (76,95); (91,78); (103,80); (113,86); (110,89); (115,123)	(9,42); (23,24); (26,27); (35,36); (44,45); (48,27); (54,56); (61,100); (64,65); (76,95); (77,78); (103,80); (110,89); (113,86); (115,123)	(17,27); (23,24); (35,36); (38,65); (41,42); (48,27); (54,56); (56,45); (76,95); (77,78); (95,100); (103,80); (110,89); (113,86); (115,123)	(9,42); (17,27); (23,24); (25,36); (44,45); (48,27); (54,56); (61,100); (64,65); (76,95); (91,78); (103,80); (110,89); (113,86); (115,123)
3	(8,24); (9,42); (17,27); (25,36); (38,65); (48,27); (56,45); (61,100); (65,56); (76,95); (91,78); (103,80); (113,86); (110,89); (115,123)	(9,42); (23,24); (26,27); (35,36); (44,45); (48,27); (54,56); (61,100); (64,65); (76,95); (77,78); (103,80); (110,89); (113,86); (115,123)	(17,27); (23,24); (35,36); (41,42); (48,27); (54,56); (56,45); (64,65); (76,95); (77,78); (95,100); (103,80); (110,89); (113,86); (115,123)	(9,42); (17,27); (23,24); (25,36); (38,65); (44,45); (48,27); (54,56); (61,100); (76,95); (91,78); (103,80); (110,89); (113,86); (115,123)