

Impacts of Operational Variability and Uncertainty on Distributed Generation Investment Planning: A Comprehensive Sensitivity Analysis

Sérgio F. Santos, Desta Z. Fitiwi, *Student Member, IEEE*, Abebe W. Bizuayehu, Miadreza Shafie-khah, *Member, IEEE*, Miguel Asensio, Javier Contreras, *Fellow, IEEE*, Carlos M. P. Cabrita, and João P. S. Catalão, *Senior Member, IEEE*

Abstract—This paper presents a comprehensive sensitivity analysis to identify the uncertain parameters which significantly influence the decision-making process in distributed generation (DG) investments and quantify their degree of influence. To perform the analysis, a DG investment planning model is formulated as a novel multi-stage and multi-scenario optimization problem. Moreover, to ensure tractability and make use of exact solution methods, the entire problem is kept as a mixed-integer linear programming optimization. A real-world distribution network system is used to carry out the analysis. The results of the analysis generally show that uncertainty as well as operational variability of the considered parameters have meaningful impacts on investment decisions of DG. The degree of influence varies from one parameter to another. But, in general, ignoring or inadequately considering uncertainty and variability in model parameters has a quantifiable cost. Hence, the analysis made in this paper can be very useful to identify the most relevant model parameters that need special attention in planning practices.

Index Terms—distributed generation, investment planning, distribution network systems, uncertainty.

I. NOMENCLATURE

A. Sets and Indices

k/Ω^k	Index/Set of DG alternatives of the same type
$m, n/\Omega^n$	Indices/Set of nodes
p/Ω^p	Index/Set of DG types

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-016434, 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, S. F. Santos gratefully acknowledges the UBI/Santander Totta doctoral incentive grant in the Engineering Faculty.

S. F. Santos, D. Z. Fitiwi, A. W. Bizuayehu, M. Shafie-khah, and J. P. S. Catalão are with INESC TEC and the Faculty of Engineering of the University of Porto, Porto 4200-465, Portugal, also with C-MAST, University of Beira Interior, Covilhã 6201-001, Portugal, and also with INESC-ID, Instituto Superior Técnico, University of Lisbon, Lisbon 1049-001, Portugal (e-mail: catalao@ubi.pt).

C. M. P. Cabrita is with CISE - Electromechatronics Systems Research Centre, University of Beira Interior, Covilha, Portugal (cabrita@ubi.pt).

J. Contreras and M. Asensio are with E.T.S. de Ingenieros Industriales, University of Castilla - La Mancha, 13071 Ciudad Real, Spain (e-mail: Javier.Contreras@uclm.es).

$s/\Omega^s, w/\Omega^w$	Indices/Sets of scenarios and snapshots, respectively
ss/Ω^{ss}	Index/Set of substations
t/Ω^t	Index/Set of planning stages ($t = 1, 2 \dots T$)
E	Existing DG
N	New DG
SS	Substation
T	Planning horizon

B. Parameters

b_{nm}	Susceptance of line $n - m$ (p.u.)
$d_{n,s,w,t}$	Electricity demand at each node (MW)
$ER_{p,k}^N, ER_{p,k}^E$	Emission rate of a new or existing generator (tons of CO ₂ /MWh)
f_{nm}^{max}	Flow limit of line $n - m$ (MW)
g_{nm}	Conductance of line $n - m$ (p.u.)
i	Interest rate
$IC_{p,k}^N$	Installation cost of DG (€)
$InvLim_t$	Available annual budget for investment (€)
$MC_{p,k}^N, MC_{p,k}^E$	Maintenance cost of new and existing DGs (€), respectively
M_{nm}	Big-M parameter corresponding to line $n - m$
N_n	Number of nodes
N_{ss}	Number of substations
$OC_{p,k}^N, OC_{p,k}^E$	Operation cost of new and existing DGs (€/MWh), respectively
$V_{nominal}$	Nominal voltage of the system (V)
$\eta_{p,k}$	Lifetime of DG (years)
$\lambda_{s,w,t}^{EMI}$	Emission price (€/tons)
$\lambda_{s,w,t}$	Average cost of electricity (€/MWh)
π_w	Weight associated to representative snapshot w (hours)
ρ_s	Probability of scenario s
$\sigma_{ss,s,w,t}$	Price of purchased electricity (€/MWh)
$v_{s,w,t}$	Penalty for unserved energy (€/MWh)
φ	DG penetration limit factor (%)

C. Variables and Functions

$f_{nm,s,w,t}$	Power flow through feeder $n - m$
$g_{p,k,n,s,w,t}^E, g_{p,k,n,s,w,t}^N$	Power generated by existing and new DG
$g_{ss,s,w,t}^{SS}$	Power purchased from upstream (grid)
$u_{p,k,n,t}^E$	Utilization indicator variable (1 if an existing generator is utilized; 0 otherwise)
$x_{p,k,n,t}^N$	Binary investment variable for DG
z_{nm}	Binary variable associated to line $n - m$ (1 if the line is connected; 0 otherwise)

EC_t^E, EC_t^N	Expected cost of energy generated by existing and new DGs (€)
EC_t^{SS}	Expected cost of purchased energy (€)
EMC_t^E, EMC_t^N	Expected cost of emissions for existing and new DGs (€)
$ENSC_t$	Expected cost of unserved energy (€)
$InvC_t^N$	Amortized NPV investment cost of DG (€)
$MntC_t^N, MntC_t^E$	Annual maintenance cost of new and existing DGs, respectively (€)
$\delta_{n,s,w,t}$	Unserved power (MW)
$\Delta V_{n,s,w,t}$	Voltage deviation at each node (kV)
$\theta_{nm,s,w,t}$	Voltage angle difference between nodes $n - m$ (radians)

II. INTRODUCTION

DRIVEN by techno-economic and environmental factors, nowadays, there is a global drive to integrate more distributed energy resources (DERs) in power systems, particularly at the distribution level. These typically include distributed generation (DG), storage technologies, and demand side management [1]. Especially, the scale of DG sources (mainly, renewables such as wind and solar) integrated in many distribution networks is steadily increasing. This trend is more likely to continue in the years to come due to the advent of emerging solutions such as active management of distribution networks [2], [3], which are expected to alleviate existing technical limitations, and facilitate smooth integration of DGs. The favorable agreement of countries in the recent climate change conference in Paris (COP21) is also expected to accelerate the integration of renewable energy sources (RESs). As a result, the level of electricity demand covered by energy coming from RESs is expected to dramatically increase, and such energy sources will play a significant role in distribution systems.

As a result, the issue of DG investment planning (DGIP) is becoming critical. This is especially more relevant in the case of insular network systems because new regulations are put in place to reduce the heavy dependence of such systems on fossil fuels for energy production. Tapping available energy resources (wind, solar, hydro, etc.) is inevitable to meet not only the increasing demand for electricity but also environmental constraints and renewable energy source (RES) integration targets set forth either globally or locally through Government initiatives.

However, the intermittent nature of most of these RESs (particularly, wind and solar) makes their integration in distribution networks a more challenging task. This is because such resources introduce significant operational variability and uncertainty to the system. Hence, the development of efficient methods and tools is mandatory to realize an optimal or a cost-efficient integration of such DGs and minimize their side effects.

In addition, the increasing level of DG integration in distribution systems is already leading to substantial changes in the traditional role of distribution systems, which has predominantly been to carry power unidirectionally from substations to consumers in a radial scheme. In other words, distribution network systems are slowly evolving from passive to active networks [2]. This paradigm shift will make sure that they are adequately equipped with the necessary, flexible and

intelligent tools which have the capability to minimize the underlining challenges of integrating DERs in such network systems, and, hence, pave the way to high level integration of DERs, RES-based DGs in particular. The advent of modern-day technological advances (such as smart grid technologies with state-of-the-art control and protection mechanisms) combined with conventional power system management systems (such as active and reactive power management tools) will make active networks effectively materialize [4].

Generally, the broad-range transformations in distribution networks are largely expected to effectively address current limitations of integrating DERs. As a result, the highly needed benefits of DERs, extensively discussed in [1] and [5], will be optimally exploited. In this regard, previous works on investment planning of DGs in distribution systems such as [6], [7] highlight the multi-faceted benefits of DGIP. In particular, the work in [7] demonstrate that “investment in DG is an attractive distribution planning option for adding flexibility to an expansion plan, mainly by deferring network reinforcements”. Other wide-range benefits of DGs have been extensively discussed in [8]–[12]. As mentioned earlier, the integration of DG in distribution systems comes with certain challenges [13]–[15]. For example, if DGs are not properly planned and operated, they can pose considerable technical problems such as reduced voltage quality and stability. However, these are expected to be adequately mitigated in active distribution networks [7].

From a modeling perspective, DGIP has been carried out in previous works jointly with distribution network expansion planning [16]–[22] or independently [6], [7], [23], [24]. Either way, the decision variables encompass the type of DG, its capacity and location as well as the time of investment when a dynamic planning scheme is adopted as in [6], [16], [17], [20]–[24]. In the context of micro-grid or autonomous/insular systems, the prospects of DG planning, scheduling and operation have been gaining attention. Authors in [25] present a community-based long-term planning tool for RESs in insular systems with an ultimate objective of maximizing social welfare perceived by the community. The work in [26] proposes a methodology for siting and sizing of DGs from a micro-grid context, and the resulting problem is solved using the prospects of particle swarm optimization and genetic algorithm methods.

Due to the inherent uncertainty and variability, stochastic programming has been used in operation and planning of distribution systems [27]–[31]. Authors in [27] propose a stochastic model for a bidding strategy in the day-ahead market of microgrids in the presence of energy storage systems, RES-based and conventional DGs. A stochastic energy management of microgrids, consisting of conventional and RES-based DGs as well as price-sensitive loads, is proposed in [28]. Similarly, the work in [29] presents a stochastic operation model to coordinate vehicle-to-grid services with energy trading in the presence of conventional and wind type DGs. Reference [30] develops a stochastic DGIP model based on a mixed integer linear programming (MILP) framework. Uncertainties related to energy price, electricity demand, wind and solar PV power outputs are accounted by forming and dividing the corresponding duration curves.

A DG allocation problem in radial distribution networks is solved using genetic algorithm in [32]. Here, uncertainty due to forecasting errors in load and generation is modeled using a fuzzy approach. A dynamic expansion planning of distribution systems with DGs is proposed in [33], and a relatively new meta-heuristic algorithm is employed to solve the resulting problem. Uncertainty and operational variability are not accounted for in this work. The use of non-exact methods such as the meta-heuristic solution methods used in [26], [32], [33] do neither guarantee global optimality nor a measure to the global optimal solution. Since DG includes intermittent energy sources, the planning model should adequately take into account the uncertainty and variability introduced as a result, including that of electricity demand. In this respect, variability in load [6], [7], [16], [17], [20]–[23], [32] and [34], electricity prices [6], [7], [16], [17], [23], wind power output [17], [23], [25], [32], solar power output [23], [25], [32], fuel prices [23], demand growth [6], [7], and DG failures [18] are among several sources of uncertainties which have been given some attention in distribution planning works in the literature. As it can be observed, dealing with the demand variability seems to be considered in many works in the literature (often with 3 to 5 demand levels) while the others are largely ignored or represented in an overly simplified manner.

The compound effect of all these relevant uncertainty and variability issues requires designing new methods and tools in order to have an optimal or a cost-efficient integration of DGs. To guide the development of such methods and tools, it is necessary to investigate first the impact of variability and/or uncertainty of different model parameters on DG investment decisions, which is the main objective of this work. Framed in this context, this paper presents a comprehensive sensitivity analysis carried out to meet the aforementioned objective. The ultimate goal is to identify those parameters which influence the decision-making process and quantify their degree of influence. To perform the analyses, a DGIP model, formulated as a multi-stage and multi-scenario optimization problem, is used. In addition, to ensure tractability and make use of exact solution methods, the entire problem is formulated as a mixed integer linear programming (MILP) optimization. The resulting DGIP problem minimizes the net present value of investment, operation and maintenance, unserved energy and emission costs taking into account a number of technical and economic constraints. Note that the problem here is formulated from the distribution system operator’s (DSO) point of view and with a particular focus on insular networks. In such networks, where there does not often exist a functional market, in addition to managing the network system, the DSO may own and operate some utility-based DGs, and/or oversee DG investments to keep reliability, stability and power quality in the system at the required levels.

The main contributions of this work include:

- An improved multi-stage and multi-scenario DGIP mathematical formulation;
- A comprehensive sensitivity analysis to investigate the effect of uncertainty and operational variability on DG investment solution.

The rest of the paper is organized as follows. In Section III, terminologies, approaches for management of uncertainty and operational variability including their definitions are briefly

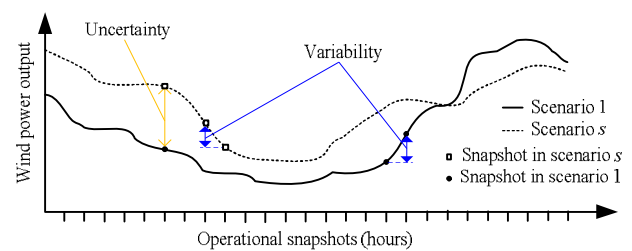


Fig. 1. Illustration of variability and uncertainty in wind power output

described. In the subsequent section, the mathematical formulation and description of the DGIP model are presented. Section V discusses the results of the case studies. The last section draws some conclusions and implications based on the outcome of the case study.

III. UNCERTAINTY AND VARIABILITY IN DGIP

A. Terminology

The terminologies uncertainty and variability are often incorrectly used interchangeably in the literature despite the fact that they are different. Variability, as defined in [35], refers to the natural variation in time of a specific uncertain parameter, whereas uncertainty refers to “the degree of precision with which the parameter is measured” or predicted. We follow these terminologies in our paper when referring to operational variability and uncertainty, which are introduced by model parameters. For example, wind power output is characterized by both phenomena; its hourly variation corresponds to the variability while its partial unpredictability (i.e. the error introduced in predicting the wind power output) is related to uncertainty. The schematic illustration in Fig. 1 clearly distinguishes both terminologies. As demonstrated in this figure, the hourly differences in wind power outputs are due to the natural variability of primary energy source (wind speed); whereas, the likelihood of having different power outputs at a given hour is a result of uncertainty (partial unpredictability) in the wind speed.

Other terminologies used in this paper are *snapshot* and *scenario*. 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) [36].

B. Sources of Uncertainty and Variability in DGIP

The various sources of uncertainties in DGIP are related to the variability and randomness of operational situations. There are some other uncertainties mostly related to the long-term price, rules, regulations and policies, etc. They can be generally categorized as random and nonrandom uncertainties [37]. The random ones are also known as high-frequency uncertainties because they correspond to situations that occur repeatedly, and hence, possess historical data. In general, they

can be characterized by probability distribution functions (PDFs), estimated by fitting the historical data. Such uncertainties have a profound impact on the operation of power distribution systems. Demand variability is one example in this category. On the other hand, nonrandom uncertainties do not occur repeatedly or they are characterized by low frequency situations; so they can hardly be statistically represented. A good example here is budget available for investment.

A well-developed DGIP tool should therefore encompass a methodology which effectively and efficiently takes into account both types of uncertainties. Exhaustive modeling of all sources of uncertainty and variability may not only be computationally unaffordable but also inefficient. Identifying the most relevant sources of uncertainty and variability for the target problem is a crucial step that should not be overlooked.

For example, consider two uncertain parameters: wind power output and emission price. Even if both are subject to uncertainty and variability, the degree of variation or uncertainty of one is totally different from the other. Apparently, the variability and uncertainty of wind power output are a lot higher than that of emission price. Hence, one would expect the former to have a higher influence on the planning outcome compared to the latter.

In this paper, the variability due to intermittent DG power outputs (mainly wind and solar) and demand are captured by considering a sufficiently large number of hourly operational states, also known here as “snapshots”. The hourly data may be historical or generated from individual or joint PDFs of uncertain parameters. To ensure problem tractability, the hourly snapshots are then reduced by means of *k-means* clustering, which leads to a substantially lower number of representative snapshots compared to the original set of data. This means each of the selected snapshots, representing a group of similar operational situations, is assigned a weight π_w proportional to the number of operational situations in its group. For instance, the wind power output profile in Fig. 1 has two profiles for the sample hours. Each day throughout the planning horizon has such profiles of its own. This means that for a horizon of three years long the number of snapshots per scenario is equal to 3×8760 . Such number of operational snapshots in each year and scenario are clustered into a predefined number of snapshot groups. In addition to the characterization of the RES power output uncertainty via scenarios (as in Fig. 1), the uncertainty regarding the evolution of the system (emission price, demand growth, etc.) is also represented by a number of scenarios (or storylines) unfolding as time passes by. Combinations of all these scenarios then form the final set of scenarios (as in Fig. 2) that are used in the analysis.

The schematic representation in Fig. 2 illustrates the multi-stage and multi-scenario DGIP modeling framework and the expansion solution structure (i.e. X_t 's). At each stage of the planning horizon, we obtain a single and robust expansion strategy which is good enough for all scenarios [36], [38]. Note that while operational variables depend on each scenario and snapshot, the investment decision variables only depend on the time stage index. This means that the investment solution obtained should satisfy all conditions in every

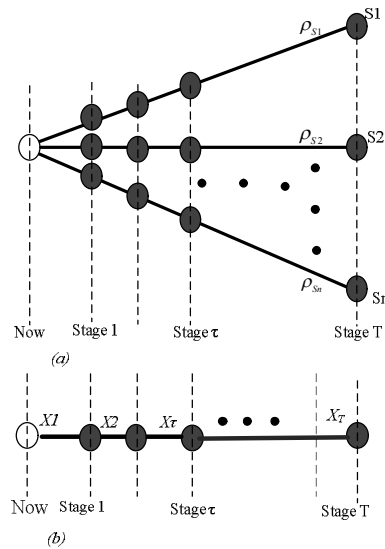


Fig. 2. A schematic representation of (a) possible future scenarios' trajectories with multiple scenario spots along the planning horizon, (b) a decision structure at each stage.

scenario, making the solution robust against any realization of the considered scenarios. It should be noted here that the robustness of the solution is directly related with the level of details of uncertainty and variability characterization. Generally, the higher the numbers of snapshots and scenarios considered are, the more robust the solution is. However, there is always a threshold beyond which adding more snapshots and scenarios does not significantly change the solution but increases unnecessary computational burden. If the scenarios considered in the planning are carefully selected to be representative enough of all possible uncertainty realizations, then, the robustness and reliability of the solution can be more guaranteed.

In this work, the evolution of carbon dioxide (CO₂) price and electricity demand growth are captured through a predefined number of scenarios, each with a certain degree of realization ρ_s . For the sake of simplicity, all scenarios are assumed to be equally probable. The effects of other sources of uncertainty such as fuel prices, and tariffs of energy generated by various DGs (both conventional and renewable power generation units) are then analyzed via sensitivity analysis.

IV. PROBLEM FORMULATION

This work focuses on investigating how sensitive DG investment decisions are with respect to variations of selected uncertain parameters. This is relevant for identifying the parameters with the highest influence on DG investment so as to design a DGIP model by adequately factoring the variability and the uncertainty of the most relevant parameters. Eventually, this helps to ensure an optimal integration of DG in network systems.

A DGIP problem is naturally dynamic because the solution has to explicitly provide the necessary information regarding when DG investments are needed. Regarding the planning horizon and decision stages, on account of the dynamic nature of the problem, a more realistic approach would be to

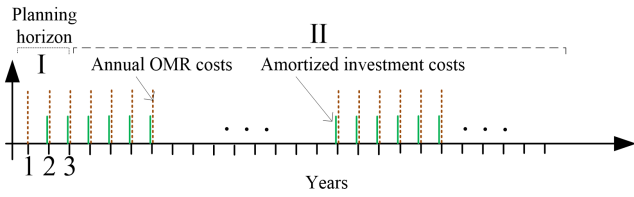


Fig. 3. Illustration of cost components within and outside the planning horizon

formulate the problem with multiple decision stages (i.e. multi-year decision framework) while accounting for all possible future scenarios. However, to ensure tractability, the numbers of stages and scenarios are usually limited.

In this work, the DGIP problem is formulated as a multi-stage and multi-scenario optimization model within a given planning window (horizon). This modeling framework assumes that there are n probable future storylines (or scenarios) each associated with a probability of realization ρ_s that stochastically represents relevant sources of uncertainties.

A. Objective Function

The resulting DGIP model, a MILP optimization problem, minimizes the sum of net present value (NPV) of four cost terms as in (1). Here, the binary investment and utilization variables as well as the operational variables such as generated power, flows, etc. constitute the set of decision variables of the optimization.

The first term in (1), TIC , represents the total NPV of the investment costs of DG, constituting conventional and various renewable energy sources, under the assumption of a perpetual planning horizon [39]. In other words, “the investment cost is amortized in annual installments throughout the lifetime of the installed DG”, as is done in [17]. The second term $TOMRC$ corresponds to the total sum of NPV: (i) operation, maintenance and reliability (OMR) costs throughout the planning stages, and (ii) the OMR costs incurred after the last planning stage. Note that the costs in (ii) rely on the OMR costs of the last planning stage and a perpetual planning horizon is assumed when spreading these costs after the last planning stage. To further clarify this, consider the illustrative example in Fig. 3. It is understood that investments are made in a specific year within the planning horizon (the second year in this case) and the investment costs are amortized throughout its lifetime. However, the OMR costs are incurred every year within and after the planning horizon. To balance these cost terms, a perpetual planning horizon, i.e. an endless payment of fixed payments is assumed. Based on the finance theory [39], the present value of perpetuity, which is the sum of the net worth of infinite annual fixed payments, is determined by dividing the fixed payment at a given period by the interest rate i . Based on this, the OMR costs include the associated annual costs within (part I) and outside the planning horizon (part II). The latter (part II) are determined by the perpetuity of the costs in the last planning stage updated by net present value factor in this case $(1+i)^{-3}$. Note that after the lifetime of the DG elapses, investments will be made in the same DG with the same cost according to the assumption of a perpetual planning horizon.

The third term $TEMC$ in (1) corresponds to the total sum of NPV emission costs in the system throughout the planning

stages and those incurred after the last planning stage under the same assumptions as in the case of OMR costs. Similarly, the last term TLC in (1) accounts for the total NPV cost of losses.

$$\text{Minimize } TC = TIC + TOMRC + TEMC + TLC \quad (1)$$

$$\begin{aligned} \text{where } TIC &= \sum_{t \in \Omega^t} (1+i)^{-t} \text{Inv}C_t^N / i; \quad TOMRC = \\ & \frac{\sum_{t \in \Omega^t} (1+i)^{-t} (MntC_t^N + MntC_t^E + EC_t^N + EC_t^E + EC_t^{SS} + ENSC_t)}{\text{NPV of investment cost}} + \\ & \frac{(1+i)^{-T} (MntC_T^N + MntC_T^E + EC_T^N + EC_T^E + EC_T^{SS} + ENSC_T) / i}{\text{NPV of operation, maintenance and reliability costs}}; \\ TEMC &= \frac{\sum_{t \in \Omega^t} (1+i)^{-t} (EMC_t^N + EMC_t^E)}{\text{Operation, maintenance and reliability costs incurred after stage } T} + \\ & \frac{(1+i)^{-T} (EMC_T^N + EMC_T^E) / i}{\text{NPV of emission costs}}; \quad \text{and } TLC = \\ & \frac{\sum_{t \in \Omega^t} (1+i)^{-t} \text{Loss}_t}{\text{Emission costs incurred after stage } T} + \frac{(1+i)^{-T} \text{Loss}_T / i}{\text{NPV of losses cost}} + \frac{\text{Losses cost incurred after stage } T}{\text{Losses cost incurred after stage } T} \end{aligned}$$

The individual cost terms in (1) are computed as follows. The NPV of the total costs is given by the sum of the amortized investment costs of DG, constituting conventional and various renewable energy sources (1.1), expected maintenance and operation cost of new (1.2, 1.4) and existing (1.3, 1.5) DGs, as well as the expected cost of unserved energy which is captured by penalizing any unserved power as in (1.6). In addition, the expected cost of emission and energy purchased from the grid (if any) are also included in the objective function (see equations 1.7 through 1.9). The cost of network losses in the system, computed as in (1.10), is also included in the objective function. Note that to keep the problem linear, the quadratic flow function in (1.10) is linearized using a first-order approximation (i.e. piecewise linearization) as in [17]. In order this paper to be self-contained, the linearized model is provided in Appendix B. Here, five piecewise linear segments are considered throughout analysis, which is in line with the findings in [40].

Notice that equation (1.1) is weighted by the capital recovery factor $\frac{i(1+i)^{\eta_{p,k}}}{(1+i)^{\eta_{p,k}} - 1}$. Besides, $x_{p,k,n,0}^N$ is defined to be zero, and the formulation in (1.1) ensures that the investment cost of each DG is considered only once in the summation. For example, suppose an investment in a particular DG is made in the fourth year of a five-year planning horizon. This means the DG will be available during the fourth and the fifth years because of the logical constraint in (8). Hence, the binary variables associated to this DG in those years will be 1 while the rest will be zero i.e. $x_{p,k,n,t}^N = \{0,0,0,1,1\}$. In this particular case, only the difference $(x_{p,k,n,4}^N - x_{p,k,n,3}^N)$ equals 1 while the remaining ones are all zero, i.e. $(x_{p,k,n,t}^N - x_{p,k,n,t-1}^N) = 0, \forall t \neq 4$, and hence the investment cost is considered only once.

$$\text{Inv}C_t^N = \sum_{n \in \Omega^n} \sum_{k \in \Omega^k} \sum_{p \in \Omega^p} \frac{i(1+i)^{\eta_{p,k}}}{(1+i)^{\eta_{p,k}} - 1} IC_{p,k}^N (x_{p,k,n,t}^N - x_{p,k,n,t-1}^N); \quad \forall t \in \Omega^t \quad (1.1)$$

$$\text{Mnt}C_t^N = \sum_{n \in \Omega^n} \sum_{k \in \Omega^k} \sum_{p \in \Omega^p} MC_{p,k}^N x_{p,k,n,t}^N; \quad \forall t \in \Omega^t \quad (1.2)$$

$$\text{Mnt}C_t^E = \sum_{n \in \Omega^n} \sum_{k \in \Omega^k} \sum_{p \in \Omega^p} MC_{p,k}^E u_{p,k,n,t}^E; \quad \forall t \in \Omega^t \quad (1.3)$$

$$EC_t^N = \sum_{s \in \Omega^S} \rho_s \sum_{w \in \Omega^W} \pi_w \sum_{n \in \Omega^n} \sum_{k \in \Omega^k} \sum_{p \in \Omega^p} OC_{p,k}^N g_{p,k,n,s,w,t}^N ; \quad (1.4)$$

$$EC_t^E = \sum_{s \in \Omega^S} \rho_s \sum_{w \in \Omega^W} \pi_w \sum_{n \in \Omega^n} \sum_{k \in \Omega^k} \sum_{p \in \Omega^p} OC_{p,k}^E g_{p,k,n,s,w,t}^E ; \quad (1.5)$$

$$ENSC_t = \sum_{n \in \Omega^n} \sum_{s \in \Omega^S} \rho_s \sum_{w \in \Omega^W} \pi_w u_{s,w,t} \delta_{n,s,w,t} ; \forall t \in \Omega^t \quad (1.6)$$

$$EMC_t^N = \sum_{s \in \Omega^S} \rho_s \sum_{w \in \Omega^W} \pi_w \sum_{n \in \Omega^n} \sum_{k \in \Omega^k} \sum_{p \in \Omega^p} \lambda_{s,w,t}^{EMI} ER_{p,k}^N g_{p,k,n,s,w,t}^N ; \quad (1.7)$$

$$EMC_t^E = \sum_{s \in \Omega^S} \rho_s \sum_{w \in \Omega^W} \pi_w \sum_{n \in \Omega^n} \sum_{k \in \Omega^k} \sum_{p \in \Omega^p} \lambda_{s,w,t}^{EMI} ER_{p,k}^E g_{p,k,n,s,w,t}^E ; \quad (1.8)$$

$$EC_t^{SS} = \sum_{s \in \Omega^S} \rho_s \sum_{w \in \Omega^W} \pi_w \sum_{ss \in \Omega^{SS}} \lambda_{ss,s,w,t} g_{ss,s,w,t}^{SS} ; \forall t \in \Omega^t \quad (1.9)$$

$$Loss_t = \sum_{s \in \Omega^S} \rho_s \sum_{w \in \Omega^W} \pi_w \sum_{n,m \in \Omega^n} \lambda_{s,w,t} \frac{g_{nm}}{(V_{nominal} * b_{nm})^2} (f_{nm,s,w,t})^2 ; \quad (1.10)$$

Equations (1.2) and (1.3) stand for the annual maintenance costs of candidate and existing DGs, respectively. These cost components are multiplied by the corresponding binary variables to determine whether each DG is being utilized or not. Note that the binary investment variable is also used for this purpose because there is no economic explanation or justification as to why it cannot be utilized immediately after an investment is made on a given asset. For the case example given above, the DG will incur maintenance costs in the last two years. For existing generators, binary variables are used to indicate their respective utilizations.

The operation costs given by (1.4) and (1.5) for candidate and existing DGs, respectively, depend on the amount of power generated for each scenario, snapshot, stage and DG type. Therefore, these costs represent the expected costs of operation. Similarly, the penalty term for the unserved power, given by (1.6), is dependent on the scenarios, snapshots and time stages. Equation (1.6) therefore gives the expected cost of unserved energy. The expected emission costs of candidate and existing generators are given by (1.7) and (1.8), respectively.

B. Constraints

i) Load balance constraints

The load balance at each node is given by equation (2).

$$\begin{aligned} \sum_{k \in \Omega^k} \sum_{p \in \Omega^p} (g_{n,p,k,s,w,t}^E + g_{n,p,k,s,w,t}^N) + \sum_{ss \in \Omega^{SS}} g_{ss,s,w,t}^{SS} \\ + \delta_{n,s,w,t} - \sum_{n,m \in \Omega^n} f_{nm,s,w,t} \\ + \sum_{n,m \in \Omega^n} f_{mn,s,w,t} \geq d_{n,s,w,t} ; \quad (2) \\ \forall s \in \Omega^S ; \forall t \in \Omega^t \end{aligned}$$

ii) Investment limits

In real problems, there always exist financial constraints;

therefore, the maximum allowable budget for investment in DGs for a given year is limited by (3).

$$\sum_{n \in \Omega^n} \sum_{k \in \Omega^k} \sum_{p \in \Omega^p} IC_{p,k}^N (x_{p,k,n,t}^N - x_{p,k,n,t-1}^N) \leq InvLim_t ; \quad (3)$$

iii) Generation capacity limits

The minimum and maximum capacity limits of existing and candidate generators are represented by (4) and (5), respectively. Note that the binary variables also appear here and multiply these bounds. This is to make sure that the power generation variable is zero when the generator remains either unutilized or unselected for investment. In the case of intermittent power source, the lower generation limits $g_{p,k,s,w,min}^E$ and $g_{p,k,s,w,min}^N$ is often set to 0 while the corresponding upper limits are set equal to the actual power output of the DG corresponding to the level of primary energy source (wind speed and solar radiation, for instance). Hence, the upper bound in this case depends on the operational state (i.e. the snapshot) and the scenario.

$$u_{p,k,n,t}^E g_{p,k,s,w,min}^E \leq g_{p,k,n,s,w,t}^E \leq u_{p,k,n,t}^E g_{p,k,s,w,max}^E ; \quad (4)$$

$$x_{p,k,n,t}^N g_{p,k,s,w,min}^N \leq g_{p,k,n,s,w,t}^N \leq x_{p,k,n,t}^N g_{p,k,s,w,max}^N ; \quad (5)$$

iv) Unserved power limit

The upper and lower limits of the unserved power are given by (6). Normally, the maximum unserved power one can have at a certain node is the demand at that node. However, the upper bound may be superfluous because, under normal circumstances, when a sufficiently large penalty factor is used in the objective function, the unserved power variable will tend to be very close to zero by optimality.

$$0 \leq \delta_{n,s,w,t} \leq d_{n,s,w,t} ; \quad (6)$$

v) DG penetration level limit

Mainly due to technical reasons, there can be a maximum penetration level of DG integration (or, equivalently saying, the maximum percentage of demand covered by DG power). This is ensured by adding the constraints in (7).

$$\sum_{n \in \Omega^n} \sum_{p \in \Omega^p} \sum_{k \in \Omega^k} (g_{p,k,n,s,w,t}^E + g_{p,k,n,s,w,t}^N) \leq \varphi d_{n,s,w,t} ; \quad (7)$$

vi) Logical constraints.

An investment already made at time stage t cannot be reversed or divested in the subsequent time stages; hence, the asset should be available for utilization immediately after the investment is made. Such constraints can be realized using (8).

$$x_{p,k,n,t}^N \geq x_{p,k,n,t-1}^N ; \quad (8)$$

vii) Network model constraints

As mentioned earlier, integrating DGs could in some cases result in technical problems in the system such as congestion, voltage rise and stability issues. Therefore, if these issues are deemed critical, it may be desirable to include network constraints so that power flows and node voltages remain within their respective permissible ranges.

To this end, a linearized network model, first proposed in [41] in the context of transmission expansion planning and further extended to distribution network system planning in [42], is used here. In distribution systems, since active power flow dominates the apparent power flow, reactive power flow can be neglected. Hence, without loss of generality, only the active power flow through a given line, given by (9), can be considered. Equation (10) ensures that the flow through the distribution lines do not exceed their corresponding thermal capacities.

$$M_{nm}(z_{nm} - 1) \leq f_{nm,s,w,t} - \{V_{nominal}(\Delta V_{n,s,w,t} - \Delta V_{m,s,w,t})g_{nm} - V_{nominal}^2 b_{nm} \theta_{nm,s,w,t}\} \leq M_{nm}(1 - z_{nm}); \quad (9)$$

$$\forall n, m \in \Omega^n; \forall s \in \Omega^s; \forall w \in \Omega^w; \forall t \in \Omega^t \\ -f_{nm}^{max} z_{nm} \leq f_{nm,s,w,t} \leq z_{nm} f_{nm}^{max}; \quad (10) \\ \forall n, m \in \Omega^n; \forall s \in \Omega^s; \forall w \in \Omega^w; \forall t \in \Omega^t$$

Note that the voltage at each node is assumed to be equal to $V_{nom} + \Delta V_{n,s,w,t}$ where $\Delta V_{n,s,w,t}$ stands for the voltage deviation at each node which is bounded as $-\varepsilon * V_{nominal} \leq \Delta V_{n,s,w,t} \leq \varepsilon * V_{nominal}$. For the analysis throughout this paper, the tolerance factor ε is set to 0.05, and the voltage magnitude and angle at all substations are set to $1.05V_{nominal}$ and 0, respectively.

viii) Radiality constraints

The traditional radiality constraint in (11) [43], along with the load balance equation, gives the necessary condition for a distribution network to be radial and connected. The analysis in this paper considers a radial network, and does not include grid expansion or switching. Therefore, equation (11) is sufficient to keep the radiality of the network and ensure that all nodes are connected.

$$\sum_{n,m \in \Omega^n} z_{nm} = N_n - N_{SS}; \quad \forall SS \in \Omega^{SS} \quad (11)$$

V. CASE STUDY DESCRIPTION

A. System Data

The system considered in the study is a real-life insular distribution network in São Miguel Island, Azores, Portugal. In this system, currently, there is no electricity market, and there is no energy imported (purchased) from the transmission grid. The system has a peak demand of 70.2 MW, and information about existing generators is shown in Table I. The investment limit in each year is set to 120 M€. The average cost of electricity $\lambda_{s,w,t}$ used for estimating cost of losses is assumed to be the average of all marginal costs of power production of DGs.

In this system, various DG types with capacities ranging from 1 to 30 MW are considered as candidates for investment (see in Table II). These fall into small- to medium-scale DG categories according to the capacity-based classification of DGs in [44]. The installation and maintenance costs of each DG are either directly obtained from [44] and [45] or estimated using the so-called six-tenths rule [46], which establishes a relationship between cost and quantity (in this case, installed capacity). This method reflects the economy of scale that exists in DGIP, i.e. the higher the installed capacities of DGs

of the same type, the lower the costs per installed kW get. The hourly series (historical data) of wind speed and solar radiation at various locations of the island are obtained from publicly available databases [47], [48], respectively. The correlation among the hourly wind speed and solar radiation series is approximately -0.13. The geographical coordinates where these data are taken from include (37.790,-25.385), (37.778,-25.489), (37.866,-25.816), (37.797,-25.170), (37.717,-25.505), (37.823,-25.487), (37.772,-25.375) and (37.782,-25.661). Then, the wind (WD) and solar photovoltaic (PV) power production series used in the simulations are determined by plugging the wind speed and the radiation data in the corresponding power curve expressions.

The DGIP problem is coded in GAMS 24.0 and solved using CPLEX 12.0. All simulations are carried out in HP Z820 Workstation with E5-2687W processor, clocking at 3.1 GHz.

B. Scenario Definition

Defining scenarios is in itself a complex problem, which requires exhaustive research and sufficient knowledge of the evolution of the system under consideration. Because of this, the number and the nature of scenarios are mostly predefined, and, to do this, planners often rely on expert knowledge. In this work, three scenarios (storylines) are defined in connection to the possible evolutions of two relevant uncertain parameters over the planning horizon, namely, electricity demand growth and emission price. Table III shows the three evolutions of demand growth, denoted as Low, Moderate and High, having an equal degree of realization. Similarly, the emission price is represented by three equally probable storylines (scenarios), as depicted in Table III. Out of these individual scenarios, assuming the two uncertain parameters are independent, we can get nine different combinations, which form the new set of scenarios used in the simulations. With this as a base-case, sensitivity analyses are carried out to study the impact of several system parameters other than these, which involve some degree of uncertainty, on DG investment decisions. These parameters include interest rate, DG penetration limit, solar PV and wind power output uncertainty, generator availability, electricity tariffs and fuel prices.

C. Impact of Network Inclusion/Exclusion on DGIP Solution

To assess the impacts on the DGIP solution, the formulated problem is solved with and without network. The former considers the entire network system but the latter assumes that the electricity demand is aggregated and connected to a hypothetical node and all generators are assumed to be connected to this node. One of the main differences lies in the network losses which are only accounted for when considering the network. However, since distribution networks span over a small geographical area, the feeders and distribution lines are usually short. Therefore, in properly designed distribution networks, power losses are negligible and, hence, they are not expected to significantly change DG investment planning solution. This argument has been experimentally verified by running simulations with and without a network on two insular networks (the distribution networks of São Miguel Island described before and La Graciosa Island presented in [49]). In both cases, the DGIP results with and without a network are

very similar, only differing in one DG investment. Moreover, the differences in total investment cost throughout a three-year planning horizon are 2.2 and 3.5%, respectively.

Generally, excluding the network slightly results in overinvestment. This is because neglecting the network would naturally mean neglecting the voltage constraints. As a result, this would lead to an increase in the size of DG integrated to the system that would otherwise be impossible when considering the network due to voltage rise issues. In the systems studied, the increase in DG investments as a result of not considering the network is negligible. Moreover, the cost of losses in both test cases is too small (accounting for less than 0.02 % of the total system cost) to have an impact on the solution. Based on these results, the sensitivity analysis here is carried out without considering the network. This is not expected to affect the analysis work since the main aim of the work here is to identify the parameters that significantly influence DGIP solutions. It should be clearly understood that the work in this paper is not to make investment decisions; it should rather be understood as an important step that provides relevant input to the development of robust planning tools. The exclusion of network (i.e. collapsing the whole system into one node) reduces the computation burden and helps one to increase the level of details of other relevant issues such as uncertainty and variability of uncertain parameters. It should however be noted that the aforementioned findings may largely depend on the size and type of system considered.

Moreover, the effect of network congestion on DG

investment decision is not accounted for when the network is neglected. Nonetheless, since DGs are placed close to the consumption points, it can be fairly assumed that congestion is less likely to occur. Other network constraints (such as voltage and angle-related ones) can be easily managed by placing some power system elements (such as reactive power sources and storage systems) at the most appropriate places.

VI. RESULTS AND DISCUSSION

The analysis results with regards to the sensitivity of investment decisions on DGs with variations of selected system parameters are presented and discussed as follows.

A. Demand Growth and CO₂ Price

The total investment cost for every combination of demand growth and emission price scenarios are shown in Table IV, along with the corresponding overall system costs as in Table V. We can see in these tables that DG investments are more sensitive to emission price uncertainty than to demand growth even if this may be case dependent. The DG investment decisions corresponding to each scenario and time stage are given in Table A.1 of Appendix A.

B. Interest Rate

The evolution of interest rate remains uncertain, and hence it is subject to change at any time in the future. To see its effect on DG investment decisions, it is changed by holding other parameters at their base case values. Generally, investments in DG fall as the interest rate increases. This is illustrated in Fig. 4, where one can clearly observe the decreasing trends of investment in DG (renewables, in particular). Their share in the total energy produced also follows a similar trend. This is in line with financial theory which states that higher interest rates deter investments because this raises the expected rate of return of an investment, which does not incentivize investments. As an example, an interest rate of 2% results in investments in all candidate DGs of wind and solar types except PV1 and PV2 (see in Table II); whereas, for an interest rate of 12%, the investments made only include PV7, PV8 and all wind type DGs. The huge difference here highlights how sensitive the investment decisions can be with respect to the interest rate.

C. DG Penetration Level Factor

DG penetration level factor is defined as the percentage of electricity demand met by DG power at a certain instant. This factor is another relevant parameter that affects the investment decisions of DGs. Intuitively, one may ponder that the higher the value of this factor, the higher the incentive for integrating more renewables, and, therefore, the higher the DG investments. But this holds only up to a certain threshold, beyond which there seems to be few or no new investments made. Fig. 5 clearly reflects this phenomenon. In the case study presented in this paper, the threshold value of the penetration level seems to be 40%. Below this level, investments made in DG steadily increase with the penetration level from almost no investments at 10% to seven investments at 40%. However, this is not the case for higher penetration levels. Even if the penetration level is set beyond 40%, no new investments are justified.

TABLE I
DATA FOR EXISTING GENERATORS

Generator type, p	Alternative, k	Installed capacity (MW)	$OC_{p,k}$ (€/MWh)	$IC_{p,k}$ (M€)	$MC_{p,k}$ (M€)	$ER_{p,k}$ (tons/MWh)
1	Hydro	Hydro	4.07	7.0	NA	0.38
2	Geothermal	GEOT	24.0	5.0	NA	1.20
3	HFO-T*	HFO	98.0	145.4	NA	0.01
4	Wind	WD 0	10.0	17.0	NA	0.80

* Heavy fuel oil turbine

TABLE II
DATA FOR CANDIDATE GENERATORS

Generator type, p	Alternative, k	Installed capacity (MW)	$OC_{p,k}$ (€/MWh)	$IC_{p,k}$ (M€)	$MC_{p,k}$ (M€)	$ER_{p,k}$ (tons/MWh)
1	Solar	PV 1	1.0	40	3.00	0.06
2	Solar	PV 2	1.5	40	3.83	0.08
3	Solar	PV 3	2.0	40	4.55	0.09
4	Solar	PV 4	2.5	40	5.20	0.10
5	Solar	PV 5	3.0	40	5.80	0.12
6	Solar	PV 6	4.0	40	6.89	0.14
7	Solar	PV 7	6.0	40	8.79	0.17
8	Solar	PV 8	10	40	11.94	0.24
9	Wind	WD 1	1.0	17	2.64	0.05
10	Wind	WD 2	2.0	17	4.00	0.08
11	Wind	WD 3	5.0	17	6.93	0.14
12	Wind	WD 4	10	17	10.51	0.21
13	CGT**	CGT 1	30	145.4	27.00	0.01
14	Biomass	BM 1	20	20	80.00	3.00

** Combustion gas turbine

TABLE III
DEMAND GROWTH AND CO₂ PRICE SCENARIOS

Stages	Demand growth scenarios			CO ₂ price scenarios (€/ton of CO ₂)		
	Low	Moderate	High	Low	Moderate	High
T0	0%	0%	0%	5	5	5
T1	2%	5%	10%	7	12	20
T2	5%	10%	20%	10	18	30
T3	7%	15%	30%	13	25	45

As can be seen in Fig. 5, the impact of DG penetration level on emissions and expected system costs is also significant. As expected, the increase in DG investments is offset by a higher decrease in operation and emission costs, leading to decreasing trends of the expected system cost and the emissions with increasing penetration level. Beyond 40%, the rate of changes in both curves is however insignificant. This may be the maximum technical penetration limit of variable energy sources in the absence of energy storage and appropriate reactive power compensation mechanisms put in place to counter the negative effects of integrating variable generation such as voltage and grid stability issues. To maintain a healthy operation of the system, high production levels of RES-based DGs need to be curtailed. The curtailment rate and level increase with the size of variable power capacity installed in the system. Hence, in this situation, further investment on such resources (beyond 40%) may not be justified because doing so does not lead to further reduction in system costs.

Alternatively, Fig. 6 shows the variation of DG investments with respect to the DG penetration level factor. The results in this figure also strengthen the fact that DG investments show some variations with an increasing level of this factor. The level of emissions gets lower as the DG penetration factor is increased up to a certain level (around 40%), beyond which the change is insignificant. This is indicative of the effect of increasing investments in DGs up to this level, which is in line with the previous statement.

As shown in Fig. 5, the DG penetration level can go as high as 70% on an instantaneous basis. However, managing high penetration levels of variable energy sources (often higher than 25% or so) is quite challenging. Especially, a 50% or more penetration level of variable energy sources may not be possible in the absence of adequate storage systems, reactive power compensation mechanisms and/or smart-grid solutions which help to maintain the power quality and system stability at standard levels. This is particularly the case in most insular systems. In the system considered in the present analysis, the actual wind and solar energy share is in the range of 23% and 27% (see Fig. 4) but instantaneous penetration levels can reach 60-70% (see Fig. 5) without jeopardizing the system's overall integrity. Depending on the operational situations of the system, this may be possible on certain occasions and impossible on others. Overall, in the absence of energy storage systems and/or other enabling mechanisms, the results in Fig. 5 also support the fact that the highest possible penetration level is around 40% (with the exception of a few instantaneous occasions). In many insular systems (for instance, Cape Verde, Ten Mile Lagoon -Australia, Crete - Greece) and interconnected systems (for instance, Portugal, Spain and Denmark), instantaneous wind penetration levels of 50% or higher have been regularly happening.

D. Fuel Prices and Electricity Tariffs

The impact of fuel prices and electricity tariffs of renewable generators are also analyzed by varying the levels of these parameters. The results of this sensitivity analysis are summarized in Table VI. As it can be seen in this table, DG investment decisions are very sensitive to fuel prices. For example, when the fuel price is considered to be 30% lower

TABLE IV
IMPACT OF DEMAND GROWTH AND CO₂ PRICE UNCERTAINTY ON DG INVESTMENTS

		CO ₂ price scenarios		
		Low	Moderate	High
Demand growth scenarios	Low	38.462	46.220	54.540
	Moderate	38.462	46.996	64.245
	High	38.462	53.078	64.757

TABLE V
VARIATION OF OBJECTIVE FUNCTION VALUE WITH DEMAND GROWTH AND CO₂ PRICE SCENARIOS

		CO ₂ price scenarios		
		Low	Moderate	High
Demand growth scenarios	Low	246.111	283.029	338.211
	Moderate	289.224	336.038	406.261
	High	375.187	442.091	543.606

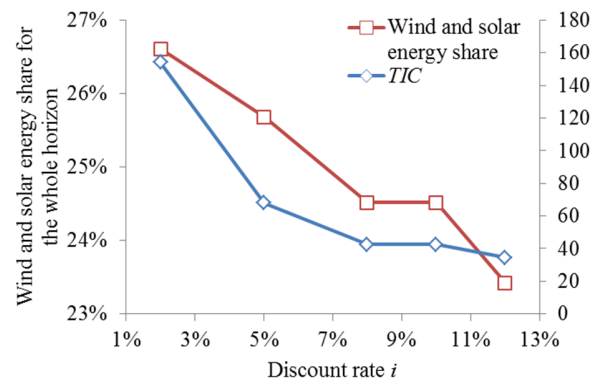


Fig. 4. Impact of interest rate on DG investments and energy production from wind and solar sources.

than that of the base case, it becomes less attractive to invest on DG (especially solar photovoltaics). But a fuel price 30% higher results in more investments in PV.

In addition to fuel prices, electricity tariffs also play a significant role in the decision-making process, particularly in the context of DG investment planning. In general terms, the price of electricity generated from wind or solar DG highly depends on the initial level of capital invested on these DG technologies. Once the investments are made, operation costs are normally very low. Nowadays, the capital costs of the main components pertaining to these technologies are continuously falling, with a learning rate of more than 20% per annum. This trend will most likely be sustained [45], resulting in a dramatically lower final cost of electricity (tariff) generated from such resources.

The effects of variations in PV energy tariffs on DG investments are especially investigated in this work. As shown in Table VI, when solar PV generators are considered to be as competitive as wind power generators, i.e. with a tariff of €20/MWh, more investments in PV are made compared to the base case. On the other hand, if the electricity tariff of energy coming from PV turns out to be twice that of the base case (€80/MWh), the number of investments made in solar PV declines.

However, this is not likely to happen given the current learning rate of solar PV technology. It is also worth mentioning that the planning solution in the case of +100% tariff for PV energy is exactly the same as the solution in the -

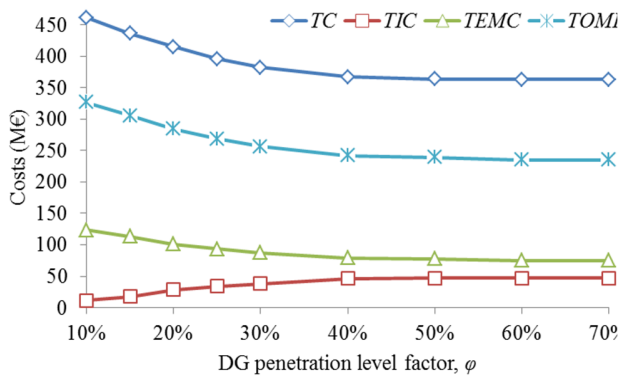


Fig. 5. Variations of emissions, investment and expected system costs with DG penetration level factor.

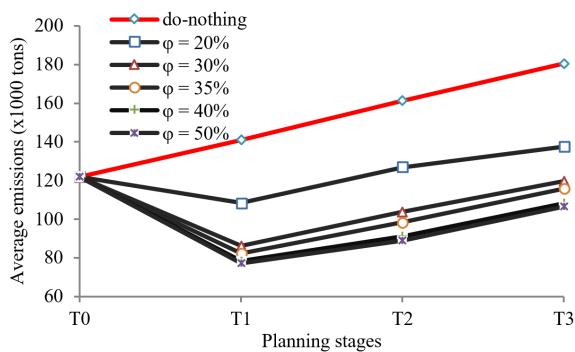


Fig. 6. Variation of DG investments with penetration level and their effect on total CO₂ emissions.

30% fuel price case, which shows the importance of energy tariff arrangement by the regulatory body.

The crowding of investment decisions in the first stage in Table VI may be due to two reasons. The first reason could be because of the absence of investment constraints related to financial and logistic matters. The second reason could be because of the relatively higher net present value of operation, maintenance and emission costs in the first stage when compared with that of any other stage. This, along with the first reason, may justify more investments to be made in the first stage rather than in any one of the subsequent stages.

E. Wind and Solar Power Output Uncertainty

To analyze the effect of uncertainty in wind and solar power outputs, two scenarios are created for each. One scenario is taken to be above the average hourly profile (roughly 30% higher than that of the base case), and the other one is taken below the average profile (approximately 30% lower than that of the base case) in each case. The results of the analysis are summarized in Table VII. One can observe that when the B-wind scenario is considered, the number of investments on wind type DGs becomes lower than these of the base case (see in Table VI). This is because of the lower yield of wind resources. In contrast, more investments are made on wind type DGs when the A-wind scenario is considered. The sensitivity of investments in solar PVs with respect to the uncertainty of PV outputs is even higher, as can be seen in this table. Note that the reasons mentioned before in the case of Table VI could explain the crowding of investments in the first stage in Table VII.

F. Demand and RES Power Output Variability

As stated earlier, the natural variation with time that exists in some of the system parameters such as demand and renewable energy source (RES) outputs leads to a large number of operational situations, adding extra complexity to the DGIP problem. Because of this, a significantly reduced number of snapshots are usually considered in such problems. For example, demand variability is commonly represented by a load duration curve, which is then aggregated into three to five load blocks. Unfortunately, this may compromise the quality of solution obtained. In light of this, we investigate how the reduction of operational situations, via clustering, affects the DG investment solution. To do this, we make use of the standard *k-means* clustering algorithm, a popular clustering analysis method in data mining, to obtain different number of data clusters (aggregates). The representative snapshot in each cluster is assumed to be the mean of the snapshots grouped together. For different number of clusters, the investments made, along with total cost and average simulation time, are summarized in Table VIII.

According to the results in this table, there seems to be a tendency to overinvest when the snapshots are further reduced. This may be due to an overestimation of the operation costs, which triggers more investments. Basically, investments are justified if the net reduction in operation costs (which may include cost of energy production, emission and losses) is higher than or equal to the overall investment costs. Based on this, if the operation costs are artificially overstated for some reason such as clustering inaccuracy, the net reduction in operation costs may seemingly be high, leading to the justification of more investments. However, it should be noted that this may not always be the case, i.e. a lower number of clusters may not necessarily be associated with an overestimation of operation costs. Depending on how the representative snapshots in all clusters are taken, the operation costs may be overestimated or underestimated, resulting in overinvestment or underinvestment, respectively.

Another important observation from Table VIII is that clustering the hourly operational snapshots in a year shows little impact on the investment solution beyond a certain threshold (which lies somewhere in the range of 300 and 400). This reflects that as far as the initially large number snapshots are clustered into 300 or more and the representative snapshots are carefully selected, the investment outcomes may not be influenced by clustering operational situations but significantly facilitate the solution process.

G. Generator Availability

It is understood that a generator can only produce power when it is available. There are two main factors which affect generator's availability: unplanned (forced) and planned (scheduled) outages. Such outages may also condition DG investment solution. Especially, more investments can be expected if, by chance, generator outages partially or fully coincide with relatively high production times of DG candidates. For example, if outages essentially occur during sunny hours, more investments could be made on solar PV candidate generators to fill in the generation gap left behind as a result of the outages. However, the chance of this happening can be very low since both processes are independent.

TABLE VI
IMPACT OF FUEL PRICE AND DG TARIFFS ON DG INVESTMENT DECISIONS

Stages	Changes in fuel price			Changes in PV energy tariff		
	+0%	-30%	+30%	-50%	+100%	
Investment in wind and solar DGs	T1	PV8, WD1, WD2, WD3, WD4	WD1, WD2, WD3, WD4	PV7, PV8, WD1, WD2, WD3, WD4	PV7, PV8, WD1, WD2, WD3, WD4	WD1, WD2, WD3, WD4
	T2	PV7	PV8	PV6	-	PV8
	T3	-	-	PV5	PV6	-
TC (M€)	364	312	412	358	372	
Total expected emissions (x 1000 tons of CO ₂)	268.8	296.4	256.5	263.1	296.4	

TABLE VII
IMPACT OF WIND AND SOLAR PV POWER OUTPUT UNCERTAINTY ON DG INVESTMENT DECISIONS

Scenarios		Time stages			TTC (M€)	TC (M€)
		T1	T2	T3		
Wind Scenarios	Below average (B)	PV8, WD2, WD3, WD4	PV7	-	44.81	412
	Above average (A)	PV8, WD1, WD2, WD3, WD4	-	-	38.46	339
Solar Scenarios	Below average (B)	PV8, WD1, WD2, WD3, WD4	-	-	38.46	373
	Above average (A)	PV8, WD1, WD2, WD3, WD4	PV7	PV6	47.00	360

TABLE VIII
IMPACT OF SNAPSHOT AGGREGATION ON DG INVESTMENT DECISIONS

Number of snapshots	TTC (M€)			TC (M€)	Average simulation time (seconds)
	Stage 1 (T1)	Stage 2 (T2)	Stage 3 (T3)		
Peak demand	47.849	6.691	5.118	-	-
100	38.462	8.533	6.082	359.45	2
300	38.462	8.533	6.082	360.66	4
324 * [17]	38.462	8.533	6.082	362.98	6
500	38.462	8.533	6.082	361.56	7
1000	38.462	8.533	6.082	362.37	21
2000	38.462	8.533	6.082	363.09	60
4000	38.462	8.533	0.000	363.55	210
6000	38.462	8.533	0.000	363.70	420
8760	38.462	8.533	0.000	363.80	720

* Snapshots are reduced according to the method in the reference

In the particular example presented earlier, the effects of forced outages of geothermal and hydro power units on the solution are analyzed. The availability series of these units are generated using a binomial distribution function, assuming generator outage rates of 15% and 10%, respectively. Note that these rates consider both types of outages.

When generating the series, an average off-time of 4 hours is factored in for both generator types. Given this input information, the DGIP problem is solved and its solution includes PV8 and all wind DG candidates in the first stage, PV7 in the second stage, and PV6 in the third stage with a total investment cost of 53.08 M€. This solution differs from that of the base case by one investment (i.e. PV6). But, in general, more investments could be justified if the generator outages occur during/around the peak hours of renewable power productions.

VII. CONCLUSIONS

This paper has presented comprehensive experimental analyses to determine the sensitivity of DG investments with variations of several uncertain parameters. The aim of such

analyses has been first to investigate the effect of variability and uncertainty in model parameters on the investment decisions of DGs, and second to identify the parameters that have the highest degree of influence on DG investments. The results of our analyses generally showed that both uncertainty and variability have a meaningful influence on DG investment decisions. In fact, the degree of influence varies from one parameter to another. Numerical results from the case study show that generator outages have little or no impact on the RES-based DG investments; whereas, uncertainty in CO₂ and fuel prices, interest rate and RES power outputs significantly influence investment decisions especially in variable energy sources. In particular, it has been found out that uncertainty in CO₂ and fuel prices as well as the interest rate seem to dramatically condition decisions compared to the uncertainty in demand growth and RES power outputs. A thorough investigation on the number of clusters of the hourly operational snapshots in a year shows that the clustering process results in little impact on the investment solution beyond a certain threshold (somewhere in the range of 300 and 400). This reflects that as far as the initially large number snapshots are clustered into 300 or more, and the representative snapshots are carefully selected, the results may not be influenced by clustering operational situations but significantly facilitate the solution process.

In general, the results revealed that ignoring or inadequately considering uncertainty and variability in model parameters has a quantifiable cost. Based on the extensive analysis, a stochastic modeling of uncertainty related to emission and fuel prices, interest rate, RES power outputs and demand growth is very critical for obtaining robust investment decisions. The comprehensive analysis performed in this work can help planners to properly weigh the effect of ignoring or considering the uncertainty and/or variability of one or more model parameters. Accordingly, a realistic planning tool considering all relevant sources of uncertainty and/or variability and solution methodologies can be developed, which leads to high quality and robust investment solutions.

APPENDIX A: DETERMINISTIC INVESTMENT SOLUTIONS

A deterministic DGIP model can be formed by allowing the DG investment variables (in the presented model) to be scenario-dependent, i.e. by assuming a given scenario happens with certainty. The investment solution of each scenario is presented in Table A.1. As it can be seen, the DG investments are particularly sensitive to the variation of CO₂ price. Note that, in Table A.1, T_i (where $i \in \{1, 2, 3\}$) denotes the time stage in which the corresponding DG is installed.

APPENDIX B: PIECEWISE LINEARIZATION

Notice that (1.10) contains quadratic flow term. For the sake of simplicity, the indices are dropped here. This quadratic term is linearized using a first-order approximation as:

$$f_{nm}^2 = \sum_{l=1}^L (2l-1) \frac{f_{nm}^{max}}{L} \Delta f_{nm,l} \quad (B.1)$$

$$f_{nm} = f_{nm}^+ - f_{nm}^- \quad (B.2)$$

$$f_{nm}^+ \geq 0; f_{nm}^- \geq 0 \quad (B.3)$$

TABLE A.1
DG INVESTMENT DECISIONS FOR EACH SCENARIO AND STAGE

Scenarios		DGs									
Demand growth	CO ₂ price	PV4	PV5	PV6	PV7	PV8	WD1	WD2	WD3	WD4	
Low	Low	0	0	0	0	T1	T1	T1	T1	T1	
Moderate	Low	0	0	0	0	T1	T1	T1	T1	T1	
High	Low	0	0	0	0	T1	T1	T1	T1	T1	
Low	Moderate	0	0	0	T3	T1	T1	T1	T1	T1	
Moderate	Moderate	0	0	0	T2	T1	T1	T1	T1	T1	
High	Moderate	0	0	T3	T2	T1	T1	T1	T1	T1	
Low	High	0	0	T2	T1	T1	T1	T1	T1	T1	
Moderate	High	T3	T3	T2	T1	T1	T1	T1	T1	T1	
High	High	T3	T2	T2	T1	T1	T1	T1	T1	T1	

$$f_{nm}^+ + f_{nm}^- = \sum_{l=1}^L \Delta f_{nm,l} \quad (B.4)$$

$$\Delta f_{nm,l} \geq \Delta f_{nm,l+1}; \forall l < L \quad (B.5)$$

where (B.1) represents the piecewise approximation of the quadratic flow variable by considering L segments. In order to use only the first quadrant of the quadratic curve (which is advantageous in terms of reducing problem complexity [40]), the flow variable is decomposed into its forward (positive) and reverse (negative) auxiliary flow variables as in (B.2). Note that both of these variables cannot be nonzero at the same time and are non-negative as enforced by (B.3). Eq. (B.4) ensures that the sum of the step-size flow variables $\Delta f_{nm,l}$ is equal to the flow. Eq. (B.5) guarantees a successive filling of the partitions.

REFERENCES

- [1] R. Poudineh and T. Jamasb, "Distributed generation, storage, demand response and energy efficiency as alternatives to grid capacity enhancement," *Energy Policy*, vol. 67, pp. 222–231, Apr. 2014.
- [2] C. L. T. Borges and V. F. Martins, "Multistage expansion planning for active distribution networks under demand and Distributed Generation uncertainties," *Int. J. Electr. Power Energy Syst.*, vol. 36, no. 1, pp. 107–116, Mar. 2012.
- [3] J. A. P. Lopes, N. Hatziargyriou, J. Mutale, P. Djapic, and N. Jenkins, "Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities," *Electr. Power Syst. Res.*, vol. 77, no. 9, pp. 1189–1203, Jul. 2007.
- [4] M. O. W. Grond, J. Morren, and J. G. Slootweg, "Integrating smart grid solutions into distribution network planning," in *PowerTech (POWERTECH), 2013 IEEE Grenoble*, 2013, pp. 1–6.
- [5] A. Yadav and L. Srivastava, "Optimal placement of distributed generation: An overview and key issues," in *2014 International Conference on Power Signals Control and Computations (EPSCICON)*, 2014, pp. 1–6.
- [6] M. E. Samper and A. Vargas, "Investment Decisions in Distribution Networks Under Uncertainty With Distributed Generation - Part I: Model Formulation," *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2331–2340, Aug. 2013.
- [7] M. E. Samper and A. Vargas, "Investment Decisions in Distribution Networks Under Uncertainty With Distributed Generation - Part II: Implementation and Results," *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2341–2351, Aug. 2013.
- [8] A. Piccolo and P. Siano, "Evaluating the Impact of Network Investment Deferral on Distributed Generation Expansion," *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1559–1567, Aug. 2009.
- [9] T. Niknam, S. I. Taheri, J. Aghaei, S. Tabatabaei, and M. Nayeripour, "A modified honey bee mating optimization algorithm for multiobjective placement of renewable energy resources," *Appl. Energy*, vol. 88, no. 12, pp. 4817–4830, Dec. 2011.
- [10] H. Hedayati, S. A. Nabaviniaki, and A. Akbarimajd, "A Method for Placement of DG Units in Distribution Networks," *IEEE Trans. Power Deliv.*, vol. 23, no. 3, pp. 1620–1628, Jul. 2008.
- [11] C. L. T. Borges and D. M. Falcão, "Optimal distributed generation allocation for reliability, losses, and voltage improvement," *Int. J. Electr. Power Energy Syst.*, vol. 28, no. 6, pp. 413–420, Jul. 2006.
- [12] M. A. Abdullah, A. P. Agalgaonkar, and K. M. Muttaqi, "Assessment of energy supply and continuity of service in distribution network with renewable distributed generation," *Appl. Energy*, vol. 113, pp. 1015–1026, Jan. 2014.
- [13] J. Liu, W. Zhang, R. Zhou, and J. Zhong, "Impacts of distributed renewable energy generations on smart grid operation and dispatch," in *2012 IEEE Power and Energy Society General Meeting*, 2012, pp. 1–5.
- [14] F. Katiraei and J. R. Agüero, "Solar PV Integration Challenges," *IEEE Power Energy Mag.*, vol. 9, no. 3, pp. 62–71, May 2011.
- [15] S. Eftekharnejad, V. Vittal, G. T. Heydt, B. Keel, and J. Loehr, "Impact of increased penetration of photovoltaic generation on power systems," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 893–901, May 2013.
- [16] M. Shivaie, M. T. Ameli, M. S. Sepasian, P. D. Weinsier, and V. Vahidiniasab, "A multistage framework for reliability-based distribution expansion planning considering distributed generations by A self-adaptive global-based harmony search algorithm," *Reliab. Eng. Syst. Saf.*, Mar. 2015.
- [17] G. Muñoz-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.
- [18] Ž. N. Popović, V. D. Kerleta, and D. S. Popović, "Hybrid simulated annealing and mixed integer linear programming algorithm for optimal planning of radial distribution networks with distributed generation," *Electr. Power Syst. Res.*, vol. 108, pp. 211–222, Mar. 2014.
- [19] M.-C. Alvarez-Herault, N. N'Doye, C. Gandioli, N. Hadjsaid, and P. Tixador, "Meshed distribution network vs reinforcement to increase the distributed generation connection," *Sustain. Energy Grids Netw.*, vol. 1, pp. 20–27, Mar. 2015.
- [20] M. Jalali, K. Zare, and M. T. Hagh, "A multi-stage MINLP-based model for sub-transmission system expansion planning considering the placement of DG units," *Int. J. Electr. Power Energy Syst.*, vol. 63, pp. 8–16, Dec. 2014.
- [21] H. Shayeghi and A. Bagheri, "Dynamic sub-transmission system expansion planning incorporating distributed generation using hybrid DCGA and LP technique," *Int. J. Electr. Power Energy Syst.*, vol. 48, pp. 111–122, Jun. 2013.
- [22] M. Sedghi, M. Aliakbar-Golkar, and M.-R. Haghifam, "Distribution network expansion considering distributed generation and storage units using modified PSO algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 52, pp. 221–230, Nov. 2013.
- [23] M. Sadeghi and M. Kalantar, "Multi types DG expansion dynamic planning in distribution system under stochastic conditions using Covariance Matrix Adaptation Evolutionary Strategy and Monte-Carlo simulation," *Energy Convers. Manag.*, vol. 87, pp. 455–471, Nov. 2014.
- [24] M. Ahmadigorji and N. Amjadi, "A new evolutionary solution method for dynamic expansion planning of DG-integrated primary distribution networks," *Energy Convers. Manag.*, vol. 82, pp. 61–70, Jun. 2014.
- [25] M. Arriaga, C. A. Canizares, and M. Kazerani, "Long-Term Renewable Energy Planning Model for Remote Communities," *IEEE Trans. Sustain. Energy*, vol. 7, no. 1, pp. 221–231, Jan. 2016.
- [26] M. V. Kirthiga, S. A. Daniel, and S. Gurunathan, "A Methodology for Transforming an Existing Distribution Network Into a Sustainable Autonomous Micro-Grid," *IEEE Trans. Sustain. Energy*, vol. 4, no. 1, pp. 31–41, Jan. 2013.
- [27] G. Liu, Y. Xu, and K. Tomsovic, "Bidding Strategy for Microgrid in Day-Ahead Market Based on Hybrid Stochastic/Robust Optimization," *IEEE Trans. Smart Grid*, vol. 7, no. 1, pp. 227–237, Jan. 2016.
- [28] G. Martinez, N. Gatsis, and G. Giannakis, "Stochastic programming for energy planning in microgrids with renewables," in *2013 IEEE 5th International Workshop on Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP)*, 2013, pp. 472–475.

[29] A. T. Al-Awami and E. Sortomme, "Coordinating Vehicle-to-Grid Services With Energy Trading," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 453–462, Mar. 2012.

[30] S. Montoya-Bueno, J. I. Muñoz, and J. Contreras, "A Stochastic Investment Model for Renewable Generation in Distribution Systems," *IEEE Trans. Sustain. Energy*, vol. 6, no. 4, pp. 1466–1474, Oct. 2015.

[31] H. Moghimi, A. Ahmadi, J. Aghaei, and A. Rabiee, "Stochastic techno-economic operation of power systems in the presence of distributed energy resources," *Int. J. Electr. Power Energy Syst.*, vol. 45, no. 1, pp. 477–488, Feb. 2013.

[32] S. Ganguly and D. Samajpati, "Distributed Generation Allocation on Radial Distribution Networks Under Uncertainties of Load and Generation Using Genetic Algorithm," *IEEE Trans. Sustain. Energy*, vol. 6, no. 3, pp. 688–697, Jul. 2015.

[33] M. Ahmadijorji and N. Amjadi, "A multiyear DG-incorporated framework for expansion planning of distribution networks using binary chaotic shark smell optimization algorithm," *Energy*, vol. 102, pp. 199–215, May 2016.

[34] 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.

[35] Gerald van Belle, *Statistical Rules of Thumb*, 2nd ed. Wiley, 2008.

[36] F. Desta Zahlay, "Strategy, Methods and Tools for Solving Long-term Transmission Expansion Planning in Large-scale Power Systems," Comillas Pontifical University, 2016.

[37] M. O. Buygi, G. Balzer, H. M. Shanechi, and M. Shahidehpour, "Market-Based Transmission Expansion Planning," *IEEE Trans. Power Syst.*, vol. 19, no. 4, pp. 2060–2067, Nov. 2004.

[38] F. Desta Zahlay, F. de Cuadra, L. Olmos, M. Rivier, and I. J. Pérez-Arriaga, "A formulation for large-scale transmission expansion planning problem and a solution strategy," in *10th International Conference on the European Energy Market (EEM)*, 2013, pp. 1–8.

[39] L. Blank and A. Tarquin, *Engineering Economy*, 7th ed. New York: McGraw-Hill Science/Engineering/Math, 2011.

[40] 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.

[41] H. Zhang, G. T. Heydt, V. Vittal, and J. Quintero, "An Improved Network Model for Transmission Expansion Planning Considering Reactive Power and Network Losses," *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 3471–3479, Aug. 2013.

[42] Sérgio F. Santos, Desta Z. Fitiwi, M. Shafie-khah, Bizuayehu A. Worke, and J. P. S. Catalão, "Optimal Sizing and Placement of Smart Grid Enabling Technologies for Maximizing Renewable Integration," in *Smart Energy Grid Engineering*, in press., 2016.

[43] 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.

[44] R. Viral and D. K. Khatod, "Optimal planning of distributed generation systems in distribution system: A review," *Renew. Sustain. Energy Rev.*, vol. 16, no. 7, pp. 5146–5165, Sep. 2012.

[45] M. Bazilian, I. Onyeji, M. Liebreich, I. MacGill, J. Chase, J. Shah, D. Gielen, D. Arent, D. Landfear, and S. Zhengrong, "Re-considering the economics of photovoltaic power," *Renew. Energy*, vol. 53, pp. 329–338, May 2013.

[46] J. Sweeting, *Project Cost Estimating: Principles and Practice*. IChemE, 1997.

[47] The World Data Center for Remote Sensing of the Atmosphere, "SOLEMI database for long-term global and direct irradiance at WDC-RSAT." [Online]. Available: <https://wdc.dlr.de> [Accessed: 02-Nov-2015].

[48] The SoDa Service, "Solar Radiation Data." [Online]. Available: <http://www.soda-is.com/eng/index.html>. [Accessed: 02-Nov-2015].

[49] G. Muñoz-Delgado, S. Montoya-Bueno, M. Asensio, J. Contreras, J. I. Muñoz, and J. M. Arroyo, "Renewable Generation and Distribution Grid Expansion Planning," in *Smart and Sustainable Power Systems*, J. P. S. Catalão, ed., CRC Press, 2015, pp. 345–404.



Sergio F. Santos received the B.Sc. and M.Sc. degrees from the University of Beira Interior (UBI), Covilhã, Portugal, in 2012 and 2014, respectively. He was a researcher between 2013 and 2015 in the EU FP7 Project SiNGULAR in Sustainable Energy Systems Lab of the same university. He is currently pursuing the Ph.D. degree under UBI / Santander Totta doctoral incentive grant in the Engineering Faculty in UBI. His research interests are in planning and operation optimization of distribution system and smart grid technologies integration.



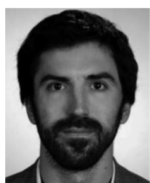
Desta Z. Fitiwi received the B.Sc. degree in Electrical and Computer Engineering from Addis Ababa University, Ethiopia, in 2005, the M.Sc. degree in Electrical and Electronics engineering from Universiti Teknologi Petronas, Tronoh, Malaysia, in 2009, and the Erasmus Mundus Joint Ph.D. degree in Sustainable Energy Technologies and Strategies (SETS), jointly offered by Comillas Pontifical University, KTH Royal Institute of Technology of Stockholm and Delft University of Technology, in 2016. He worked as a Supervisory Control and Data Acquisition (SCADA) and Adaptation Engineer in the Ethiopian Load Dispatch Center Project from 2005 to 2007. He actively participated in the realization of four EU-funded projects. He is currently working as a researcher at University of Beira Interior, Covilhã, Portugal. His research interests include regulation and economics of the power industry, transmission expansion planning, sustainable energy modeling and strategic planning, artificial-intelligence applications and mathematical optimizations for power systems.



Abebe W. Bizuayehu (M'15) received the M.Sc. degree in mechanical engineering, in the specialty of industrial mechanic from José Antonio Echevarría Higher Polytechnic Institute (I.S.P.J.A.E.), Havana, Cuba, in 1989, and the Ph.D. degree in Renewable Energy and Energetic Efficiency from the University of Zaragoza, Spain, in 2012. He received his postdoc from the University of Beira Interior (UBI) Covilha, Portugal in 2015, while working on the EU-funded FP7 project SiNGULAR.



Miadreza Shafie-khah (S'08, M'13) received the M.Sc. and Ph.D. degrees in electrical engineering from Tarbiat Modares University, Tehran, Iran, in 2008 and 2012, respectively. He received his first postdoc from the University of Beira Interior (UBI), Covilha, Portugal in 2015, while working on the EU-funded FP7 project SiNGULAR. He is currently pursuing his second postdoctoral studies in the University of Salerno, Salerno, Italy. His research interests include power market simulation, market power monitoring, power system optimization, operation of electricity markets, price forecasting and smart grids.



Miguel Asensio received the M.Sc. degrees in electrical engineering and power systems from the Polytechnic University of Madrid, Madrid, Spain, in 2003, and Comillas University, Madrid, in 2013, respectively, and the Ph.D. degree from the University of Castilla-La Mancha, Ciudad Real, Spain, in 2016. From 2003 to 2012, he was with the German, Italian, and Spanish Electrical Sector. His current research interests include decision-making support systems in the energy sector, electricity market, and operational issues and transmission pricing.



Javier Contreras (SM'05, F'15) received the B.S. degree in electrical engineering from the University of Zaragoza, Zaragoza, Spain, in 1989, the M.Sc. degree from the University of Southern California, Los Angeles, in 1992, and the Ph.D. degree from the University of California, Berkeley, in 1997.

He is currently Full Professor at the University of Castilla-La Mancha, Ciudad Real, Spain. His research interests include power systems planning, operations and economics, and electricity markets.



Carlos M. P. Cabrita was born in Lisbon, Portugal on July 2, 1951. He received the E. E. Diploma and the PhD on E. E. from the Technical University of Lisbon, Lisbon, Portugal, in 1976 and 1988, respectively. He was with Technical University of Lisbon, from 1978 to 1996. He has been with the University of Beira Interior since 1997, where he is currently Full Professor in the Department of Electromechanical Engineering. His

research interests are focused on electrical machines design and maintenance processes. He has published about 250 papers in technical journals and conference proceedings.



João P. S. Catalão (M'04-SM'12) received the M.Sc. degree from the Instituto Superior Técnico (IST), Lisbon, Portugal, in 2003, and the Ph.D. degree and Habilitation for Full Professor ("Agregação") from the University of Beira Interior (UBI), Covilha, Portugal, in 2007 and 2013, respectively.

Currently, he is a Professor at the Faculty of Engineering of the University of Porto (FEUP), Porto, Portugal, and Researcher at INESC TEC, INESC-ID/IST-UL, and C-MAST/UBI. He was the Primary Coordinator of the EU-funded FP7 project SiNGULAR ("Smart and Sustainable Insular Electricity Grids Under Large-Scale Renewable Integration"), a 5.2-million-euro project involving 11 industry partners. He has authored or coauthored more than 480 publications, including 160 journal papers, 281 conference proceedings papers, 23 book chapters, and 14 technical reports, with an *h*-index of 28 and over 3045 citations (according to Google Scholar), having supervised more than 45 post-docs, Ph.D. and M.Sc. students. He is the Editor of the books entitled *Electric Power Systems: Advanced Forecasting Techniques and Optimal Generation Scheduling* and *Smart and Sustainable Power Systems: Operations, Planning and Economics of Insular Electricity Grids* (Boca Raton, FL, USA: CRC Press, 2012 and 2015, respectively). His research interests include power system operations and planning, hydro and thermal scheduling, wind and price forecasting, distributed renewable generation, demand response and smart grids.

Prof. Catalão is an Editor of the IEEE TRANSACTIONS ON SMART GRID, an Editor of the IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, and an Associate Editor of the *IET Renewable Power Generation*. He was the Guest Editor-in-Chief for the Special Section on "Real-Time Demand Response" of the IEEE TRANSACTIONS ON SMART GRID, published in December 2012, and the Guest Editor-in-Chief for the Special Section on "Reserve and Flexibility for Handling Variability and Uncertainty of Renewable Generation" of the IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, published in April 2016. He was the recipient of the 2011 Scientific Merit Award UBI-FE/Santander Universities and the 2012 Scientific Award UTL/Santander Totta. Also, he has won 4 Best Paper Awards at IEEE Conferences.