A New Dynamic and Stochastic Distributed Generation Investment Planning Model with Recourse

Desta Z. Fitiwi, Sérgio F. Santos, Abebe W. Bizuayehu, Miadreza Shafie-khah, João P. S. Catalão
Faculty of Engineering of the Univ. of Porto, Porto, Univ. of Beira Interior, Covilha,
and INESC-ID, Inst. Super. Tecn., Univ. of Lisbon, Lisbon, Portugal
dzf@ubi.pt; sdfsantos@gmail.com; buzeabebe@gmail.com; miadreza@ubi.pt; catalao@ubi.pt

***Abstract*—This paper presents a new dynamic and stochastic decision supporting model for distributed generation investment planning (DGIP). The model is formulated as a mixed integer linear programming (MILP) optimization problem that simultaneously minimizes emission, operation and maintenance, as well as reliability costs. One of the salient features of the model is that it is based on a two-period planning horizon: a short-term planning period that requires robust decisions to be made and a medium to long-term one involving exploratory or flexible investment decisions. Each period has multiple decision stages. The operational variability introduced by intermittent generation sources and electricity demand are accounted for via probabilistic methods. To ensure computational tractability, the associated operational states are reduced via a clustering technique. Moreover, uncertainties related to emission price, demand growth and the unpredictability of intermittent generation sources are taken into account stochastically. A real-life distribution network system is used as a case study, and the results of our analyses generally show the efficacy of the proposed model.**

Keywords*—*Distributed generation; DG investment planning; distribution network systems; stochastic programming; uncertainty.

I. Nomenclature

i) Sets and Indices

$k\ (\Omega^k)$	Index (Set) for DG alternatives of the same type
$p\ (\Omega^p)$	Index (Set) for DG types
$s\ (\Omega^s)$	Index (Set) for scenarios
$ss\ (\Omega^{ss})$	Index (Set) for substations
$t\ (\Omega^t)$	Index (Set) for planning stages ($t = 1, 2\ldots T$)
$w\ (\Omega^w)$	Index (Set) for snapshots
$N1$	DG investment pool for the first period
$N2$	DG investment pool for the second period
$\tau\ (\Omega^{T1})$; $\zeta(\Omega^{T2})$	Indices (Sets) of decision stages in period T1 and T2, respectively

ii) Parameters

$d_{s,w,t}$	Electricity demand (MW)
$ER^N_{p,k}, ER^E_{p,k}$	Emission rate of new or existing generator (tons/MWh)
i	Interest rate (%)
$IC^N_{p,k}$	Investment cost of DG (€)
$InvLim$	Maximum available budget for investment (€)
$MC^N_{p,k}, MC^E_{p,k}$	Maintenance cost of new or existing (€)
$OC^N_{p,k}, OC^E_{p,k}$	Operation cost of new or existing (€/MWh)
α, β, γ	Weights for balancing the cost terms
$\eta_{p,k}$	Lifetime of DG (years)
$\mu^{EM}_{s,w,t}$	Emission price (€/tons)
π_w	Weight associated to snapshot w
ρ_s	Probability of scenario s
$\sigma_{ss,s,w,t}$	Price of purchased electricity (€/MWh)
φ	DG penetration limit factor (%)

iii) Variables

$g^{SS}_{ss,s,w,t}$	Power purchased from upstream (grid)
$g^E_{p,k,s,w,t}, g^N_{p,k,s,w,t}$	Power generated by existing or new generator
EC^{SS}_t	Cost of purchased energy
EMC^E_t, EMC^N_t	Emission cost of existing or new DGs
$ENSC_t$	Cost of unserved power
IC^N_t	Investment cost of DGs
MC^N_t, MC^E_t	Annual maintenance cost of new and existing DGs
OC^N_t, OC^E_t	Operation cost of new and existing DGs
$u1^E_{p,k,\tau}$	Indicator variable of utilization of existing generators in 1st period
$u2^E_{p,k,s,\zeta}$	Indicator variable of utilization of existing generators in 2nd period
$x^{N1}_{p,k,\tau}$	DG investment binary variable in 1st period
$xx^{N1}_{p,k,s,\zeta}$	A binary variable for possible postponement of DG investment to 2nd period
$y^{N2}_{p,k,s,\zeta}$	DG investment binary variable in 2nd period
$\delta_{s,w,t}$	Unserved power

II. Introduction

Driven by the compounded effect of several techno-economic and environmental factors, integrating distributed generation (DG) sources (in particular, renewable energy sources such as wind and solar) in distribution networks (DN) has been gaining a significant momentum since recently [1]. The increasing trend of DG integration is more likely to continue in the years to come due to the advent of emerging solutions such as the active management of distribution networks [2], which are expected to facilitate smooth integration of DG's by alleviating existing technical limitations.

The share of DG energy in the overall energy mix i.e. the electricity demand covered by energy coming from DG (renewable energy sources, in particular) will gradually increase. Hence, such energy sources will play an important role in distribution network systems, and the prospect of DG investment planning (DGIP) definitely becomes more relevant in such systems. This is because tapping energy resources (wind, solar, hydro, geothermal, etc.) available in close proximity to traditional consumers is inevitable not only to meet an increasing demand for electricity but also to fulfill environmental constraints and renewable energy source (RES) integration targets set forth either globally or locally through Government initiatives.

However, the power generated from some of the DG sources (for example, the renewable energy sources such as solar and wind) is subject to variability and uncertainty.

As a result, integrating such resources in power systems introduces a significant operational variability and uncertainty. Besides, there are several other parameters subject to high-level uncertainty. The combination of all these relevant issues makes the operation and the planning process of distribution systems more complex. In order to overcome this complexity, and hence, support the decision-making process in realizing an optimal integration of DG, effective methods and tools need to be developed.

This paper presents a new dynamic and stochastic DGIP model to support the aforementioned decision-making process. The model is formulated as a mixed integer linear programming (MILP) optimization problem that simultaneously minimizes emission, operation and maintenance as well as reliability costs. One of the salient features of the model is that it is based on a two-period planning horizon. The first one is characterized by robust short-term investment decisions made in the face of uncertainty while the second one involves exploratory or flexible investment decisions to be made depending on the scenario unveiled in a medium to long-term time span. Each period has multiple decision stages. The operational variability introduced by intermittent generation sources and electricity demand are accounted for via probabilistic methods. To ensure computational tractability, the associated operational states are reduced via a clustering technique. Moreover, uncertainties related to emission price, demand growth and the unpredictability of intermittent generation sources are taken into consideration stochastically.

III. Literature Review

Distribution network systems are expected to undergo broad-range transformations in the near future so that current limitations of integrating DG (especially renewables) are effectively addressed. As a result, the highly needed benefits of DGs, extensively discussed in [3], can be optimally exploited. In this regard, previous works on investment planning of DG in distribution networks, such as [4] and [5], highlight the multi-faceted benefits of DGIP. In particular, the latter work 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 DG have been extensively discussed in [6]–[10]. In fact, the integration of DG in distribution systems also has some challenges [11]–[13]. For example, if DG's are not properly planned and operated, they can pose technical problems in the system. However, these are expected to be adequately mitigated in active DN [5].

From a modeling perspective, DGIP in previous works is carried out either jointly with distribution network expansion planning [14]–[20] or independently [4], [5], [21], [22].

Either way, the decision variables of the optimization 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 [4], [14], [15], [18]–[22].

Since DG includes intermittent energy sources, the planning model should adequately take account of the uncertainty and the variability of such sources, including that of the electricity demand. In this respect, uncertainties in load [4], [5], [14], [15], [18]–[21], electricity price [4], [5], [14], [15], [21], wind power output [15], [21], solar power output [21], fuel price [21], demand growth [4], [5], and failures in DG [16] are among several sources of uncertainties, which have been given attention in the literature related to distribution planning works.

As it can be observed, dealing with the variability, but not the uncertainty, pertaining to electricity demand seems to be considered in the literature, often by dividing the hourly load duration curve for a year into 3 to 5 demand levels, while the others are largely ignored or represented in an overly simplified manner.

IV. Problem Formulation

The work here focuses on the formulation a DGIP model considering the variability and the uncertainty of the most relevant model parameters. This model is then used as a decision-supporting tool in the optimal integration of DG in distribution network systems. In addition to the variability and uncertainty management issues, the DGIP formulation involves other relevant aspects. First, the DGIP problem is characterized by its dynamic nature because the DGIP solution has to include when DG investments are needed. Second, concerning the planning horizon and the decision stages, a more realistic approach is to formulate the problem with multiple decision stages (i.e. a multi-year decision framework) while accounting for all possible future scenarios. Here, to ensure tractability, the numbers of stages and scenarios have to be limited.

In this work, the DGIP problem is formulated as a multi-stage and multi-scenario optimization model within a two-window (period) planning framework. The first window is characterized by robust short-term investment decisions made in the face of uncertainty while the second one involves scenario-dependent decisions, which can be alternatively understood as exploratory or flexible investment decisions in a medium to long-term time span. Each period has multiple decision stages. Note that the modeling framework here 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 objective function of the DGIP model formulated in this paper is to minimize the weighted sum of net present value (NPV) of three cost terms as in (1). The first term in (1) represents the NPV of total investment costs of DGs, which constitute conventional and various renewable energy sources, under the assumption of perpetual planning horizon [23]. In other words, "the investment cost is amortized in annual installments throughout the lifetime of the installed DG", as is done in [15].

The second term corresponds to the sum of the NPV of (i) operation, maintenance and reliability (OMR) costs throughout the planning horizon, 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 [15]. The last term in (1) corresponds to the sum of the NPV emission costs in the system, and those incurred after the last planning stage under the same assumptions as in the case of OMR costs. Note that the three weights in (1) (i.e. α, β and γ) are all assumed to be 1, but depending on the degrees of relevance of the cost components in the objective function, different weights may be considered.

The NPV of total costs is then given by the sum of amortized investment costs in DGs, constituting conventional and various renewable energy sources (2), expected maintenance and operation cost of candidate DGs as in Eqs. (3) and (5), expected maintenance and operation cost of existing DGs as in Eqs. (4) and (6), as well as the expected cost of reliability which is captured by penalizing any unserved power as in (7). In addition, the expected cost of emission and energy purchased from the grid are also included in the objective function as can be seen in Eqs. (8)—(10).

Eq. (2) represents the total investment costs weighted by the capital recovery factor, $\frac{i(1+i)^{\eta_{p,k}}}{(1+i)^{\eta_{p,k}}-1}$. Note that $x^N_{p,k,0}$is defined to be zero, and the formulation in (2) ensures that the investment cost of each DG is considered only once in the summation. Eqs. (3) and (4) stand for the annual maintenance costs of candidate and existing DGs, respectively.

These cost terms 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 in the case of candidate DGs. The operation costs, given by (5) and (6) for candidate and existing DGs, respectively, depend on the amount of power generated for each scenario, snapshot, stage and DG type. Therefore, they are weighted by the probabilities of scenarios, resulting in the expected cost of operation. Similarly, Eq. (7) gives the expected cost of unserved energy. Eqs. (8) and (9) represent the expected emission costs of candidate and existing generators, respectively. The expected cost of energy purchased from upstream (i.e. from grid), is also given by (10).

$$
\begin{aligned}
&Minimize\ TC \\
&= \alpha \underbrace{\sum_{t\epsilon\Omega^t} \frac{(1+i)^{-t}}{i} IC_t^N}_{NPV\ of\ investment\ cost} \\
&+ \beta \underbrace{\sum_{t\epsilon\Omega^t} (1+i)^{-t}\ (MC_t^N + MC_t^E + OC_t^N + OC_t^E + EC_t^{SS} + ENSC_t)}_{NPV\ of\ operation,\ maintenance\ and\ reliability\ costs} \\
&+ \beta \underbrace{\frac{(1+i)^{-T}}{i} (MC_T^N + MC_T^E + OC_T^N + OC_T^E + EC_T^{SS} + ENSC_T)}_{Spreading\ operation,\ maintenance\ and\ reliability\ costs} \\
&+ \gamma \underbrace{\sum_{t\epsilon\Omega^t} (1+i)^{-t}\ (EMC_t^N + EMC_t^E)}_{NPV\ of\ emission\ costs} \\
&+ \gamma \underbrace{\frac{(1+i)^{-T}}{i} (EMC_T^N + EMC_T^E)}_{Spreading\ emission\ costs} \qquad (1)
\end{aligned}
$$

$$
\begin{aligned}
IC_t^N = &\sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} \frac{i(1+i)^{\eta_{p,k}}}{(1+i)^{\eta_{p,k}} - 1} IC_{p,k}^{N1} (x_{p,k,\tau}^{N1} - x_{p,k,\tau-1}^{N1}) \\
&+ \sum_{s\epsilon\Omega^s} \rho_s \sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} \frac{i(1+i)^{\eta_{p,k}}}{(1+i)^{\eta_{p,k}} - 1} IC_{p,k}^{N1} \big(xx_{p,k,s,\zeta}^{N1} \\
&- xx_{p,k,s,\zeta-1}^{N1}\big) \\
&+ \sum_{s\epsilon\Omega^s} \rho_s \sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} \frac{i(1+i)^{\eta_{p,k}}}{(1+i)^{\eta_{p,k}} - 1} IC_{p,k}^{N2} (y_{p,k,s,\zeta}^{N2} \\
&- y_{p,k,s,\zeta-1}^{N2}) \qquad ;\ \forall \tau \in \Omega^{T1};\ \forall \zeta \in \Omega^{T2} \qquad (2)
\end{aligned}
$$

$$
\begin{aligned}
MC_t^N = &\sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} MC_{p,k}^{N1}\, x_{p,k,t}^{N1} + \sum_{s\epsilon\Omega^s} \rho_s \sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} MC_{p,k}^{N1}\, xx_{p,k,s,\zeta}^{N1} \\
&+ \sum_{s\epsilon\Omega^s} \rho_s \sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} MC_{p,k}^{N2}\, y_{p,k,s,\zeta}^{N2} \qquad (3)
\end{aligned}
$$

$$
MC_t^E = \sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} MC_{p,k}^E\, u1_{p,k,\tau}^E + \sum_{s\epsilon\Omega^s} \rho_s \sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} MC_{p,k}^E\, u2_{p,k,s,\zeta}^E \quad (4)
$$

$$
\begin{aligned}
OC_t^N = &\sum_{s\epsilon\Omega^s} \rho_s \sum_{w\epsilon\Omega^w} 8760 * \pi_w \sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} OC_{p,k,s,w,\tau}^{N1} g_{p,k,s,w,\tau}^{N1} \\
&+ \sum_{s\epsilon\Omega^s} \rho_s \sum_{w\epsilon\Omega^w} 8760 \\
&* \pi_w \sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} OC_{p,k,s,w,\zeta}^{N2} g_{p,k,s,w,\zeta}^{N2} \qquad (5)
\end{aligned}
$$

$$
OC_t^E = \sum_{s\epsilon\Omega^s} \rho_s \sum_{w\epsilon\Omega^w} 8760 * \pi_w \sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} OC_{p,k,s,w,t}^E g_{p,k,s,w,t}^E \qquad (6)
$$

$$
ENSC_t = \sum_{s\epsilon\Omega^s} \rho_s \sum_{w\epsilon\Omega^w} 8760 * \pi_w \upsilon_{s,w,t} \delta_{s,w,t} \qquad (7)
$$

$$
\begin{aligned}
EMC_t^N = &\sum_{s\epsilon\Omega^s} \rho_s \sum_{w\epsilon\Omega^w} 8760 * \pi_w \sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} \mu_{s,w,t}^{EMI}\, ER_{p,k}^{N1}\, g_{p,k,s,w,t}^{N1} \\
&+ \sum_{s\epsilon\Omega^s} \rho_s \sum_{w\epsilon\Omega^w} 8760 \\
&* \pi_w \sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} \mu_{s,w,\zeta}^{EMI}\, ER_{p,k}^{N2}\, g_{p,k,s,w,\zeta}^{N2} \qquad (8)
\end{aligned}
$$

$$
EMC_t^E = \sum_{s\epsilon\Omega^s} \rho_s \sum_{w\epsilon\Omega^w} 8760 * \pi_w \sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} \mu_{s,w,t}^{EMI}\, ER_{p,k}^E\, g_{p,k,s,w,t}^E \qquad (9)
$$

$$
EC_t^{SS} = \sum_{s\epsilon\Omega^s} \rho_s \sum_{w\epsilon\Omega^w} 8760 * \pi_w \sum_{ss\Omega^{ss}} \sigma_{ss,s,w,t} g_{ss,s,w,t}^{SS} \qquad (10)
$$

B. Constraints

1) Load balance constraints: The sum of total generation and unserved power should be equal to the demand as in (11).

$$
\begin{aligned}
&\sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} (g_{p,k,s,w,t}^E + g_{p,k,s,w,t}^{N1}) + \sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} g_{p,k,s,w,\zeta}^{N2} + \sum_{ss\Omega^{ss}} g_{ss,s,w,t}^{SS} \\
&\quad + \delta_{s,w,t} = d_{s,w,t} \qquad (11)
\end{aligned}
$$

2) Investment limits: The budget constraints for DG investment in every year is often set, as in (12) and (13).

$$
\sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} IC_{p,k}^{N1} (x_{p,k,\tau}^{N1} - x_{p,k,\tau-1}^{N1}) \le InvLim_\tau \qquad (12)
$$

$$
\begin{aligned}
&\sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} IC_{p,k}^{N1} (y_{p,k,s,\zeta}^{N2} - y_{p,k,s,\zeta-1}^{N2}) + \sum_{k\epsilon\Omega^k} \sum_{p\epsilon\Omega^p} IC_{p,k}^{N1} (xx_{p,k,s,\zeta}^{N1} \\
&\quad - xx_{p,k,s,\zeta-1}^{N1}) \le InvLim_{s,\zeta} \qquad (13)
\end{aligned}
$$

3) Generation capacity limits: The minimum and the maximum capacity limits of any generator should be respected at all time. Eqs. (14) and (15) enforce such constraints for existing DGs in the first and the second periods, respectively. Similarly, in the case of candidate DGs, (16) through (18) are included. Note that the binary variables also multiply the corresponding capacity limits of a given generator. This is to make sure the power generation variable is zero when the generator remains either unutilized or unselected for investment. For technical reasons, the power that is purchased from the transmission grid could have minimum and maximum limits, as in (19).

$$
\begin{aligned}
u1_{p,k,\tau}^E G_{p,k,s,w,min}^E &\le g_{p,k,s,w,\tau}^E \le u1_{p,k,\tau}^E G_{p,k,s,w,max}^E && (14)\\
u2_{p,k,\zeta}^E G_{p,k,s,w,min}^E &\le g_{p,k,s,w,\zeta}^E \le u2_{p,k,\zeta}^E G_{p,k,s,w,max}^E && (15)\\
x_{p,k,t}^{N1} G_{p,k,s,w,min}^{N1} &\le g_{p,k,s,w,t}^{N1} \le x_{p,k,t}^{N1} G_{p,k,s,w,max}^{N1} && (16)\\
xx_{p,k,s,\zeta}^{N1} G_{p,k,s,w,min}^{N1} &\le g_{p,k,s,w,\zeta}^{N1} \le xx_{p,k,s,\zeta}^{N1} G_{p,k,s,w,max}^{N1} && (17)\\
y_{p,k,s,\zeta}^{N2} G_{p,k,s,w,min}^{N2} &\le g_{p,k,s,w,\zeta}^{N2} \le y_{p,k,s,\zeta}^{N2} G_{p,k,s,w,max}^{N2} && (18)\\
g_{ss,t}^{SS,min} &\le g_{ss,s,w,t}^{SS} \le g_{ss,t}^{SS,max} && (19)
\end{aligned}
$$

4) Unserved power limit: The unserved power cannot exceed the total demand. Eq. (20) represents this constraint.

$$
0 \le \delta_{s,w,t} \le d_{s,w,t} \qquad (20)
$$

5) DG penetration level limit: Due to technical reasons, there can be a maximum penetration level of DGs (or, equivalently saying, the maximum percentage of demand covered by DGs). This is ensured by adding the constraints in (21).

$$
\sum_{p\epsilon\Omega^p} \sum_{k\epsilon\Omega^k} (\, g_{p,k,s,w,t}^E + g_{p,k,s,w,t}^{N1}) + \sum_{p\epsilon\Omega^p} \sum_{k\epsilon\Omega^k} g_{p,k,s,w,\zeta}^{N2} \le \varphi d_{s,w,t} \qquad (21)
$$

6) Logical constraints: Normally, an investment made at stage *t* cannot be reversed or divested in the subsequent stages; hence, the asset should be available for utilization after the investment is made. Such condition can be realized using the set of constraints in (22)—(24).

$$
\begin{aligned}
x_{p,k,\tau}^{N1} \ge x_{p,k,\tau-1}^{N1}\ ;\ x_{p,k,\zeta}^{N1} = x_{p,k,T1}^{N1} && (22)\\
xx_{p,k,s,\zeta}^{N1} \ge xx_{p,k,s,\zeta-1}^{N1}\ ;\quad xx_{p,k,s,T1}^{N1} = x_{p,k,T1}^{N1} && (23)\\
y_{p,k,s,\zeta}^{N2} \ge y_{p,k,s,\zeta-1}^{N2}\ ;\ y_{p,k,s,T1}^{N2} = 0 && (24)
\end{aligned}
$$

V. UNCERTAINTY AND VARIABILITY IN DGIP

A. Modeling Uncertainty and Operational Variability

The various sources of uncertainties in DGIP are related to the variability and the uncertainty of operational situations.

There are some other uncertainties mostly related to the long-term price, rules, regulations and policies, etc. Variability, as defined in [24], 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. The sources of variability can be generally categorized as random and nonrandom [25]. The random ones are also known as high-frequency uncertainties because they correspond to situations that occur repeatedly, and hence, introduce significant operational variability in the power distribution systems. On the other hand, nonrandom uncertainties do not occur repeatedly or they are characterized by low frequency situations.

A well-developed DGIP tool should therefore encompass a methodology that effectively and efficiently takes account of relevant sources of uncertainty and variability. Exhaustive modeling of all sources of uncertainty and variability may not only be computationally unaffordable but also inefficient. In this paper, a sufficiently large number of operational situations are taken to account for the variability introduced by various uncertain parameters such as demand and intermittent power sources. Then, a standard clustering technique is used to reduce the number of operational states so that the problem at hand is tractable. Here, each of the reduced operational states should adequately represent a group of similar operational situations; and hence, is assigned with a probability proportional to the number of operational situations in its group.

The unpredictable nature of renewable energy sources, demand growth and low-frequency uncertainties such as emission price are stochastically considered by enumerating an adequate number of scenarios.

VI. Case Study, Results and Discussion

A. Data Used for the Case Study and Assumptions

The DGIP optimization problem is coded in GAMS 24.0 and solved using CPLEX 12.0. The system considered in the study is a distribution network of the Azores Island, which has a peak demand of 70 MW. In this system, various DG types with capacities ranging from 1 to 30 MW are considered as candidates for investment (see in Table I). The installation and maintenance cost figures of each candidate DG considered in the case study are depicted in Table I. The data for existing generators can be found in [26]. The hourly series of wind (WD) and solar photovoltaic (PV) power production for one year are obtained from various locations in the island.

B. Scenario Definition

In this work, 81 scenarios (storylines) are defined in connection to the possible evolutions of four relevant uncertain parameters over the planning horizon: demand growth, emission price, wind and solar PV power output uncertainties. Table II shows the three evolutions of demand growth, denoted as Low, Moderate and High, having equal degree of realization. Similarly, the emission price is represented by three equally probable storylines (scenarios), as shown in Table II. Three different scenarios are considered for each remaining parameters. Assuming all four parameters are independent, one gets 81 different combinations (scenarios). Note that, for the sake of simplicity, only CO_2 emissions are considered in this study, and the emission prices throughout the second period are held the same as in the third stage.

C. Case Study and Results

Table III presents the investment outcome at each stage of each planning period. As it can be observed in this table, majority of the investments tend to be made in the beginning of each period (i.e. the first and the fourth stages, in particular). This phenomenon is rather expected, because the NPV of operation and emission costs is higher in the foremost stages of the planning horizon. Hence, it becomes more attractive to invest in the leading stages so that such costs are reduced in the short-run as well as in the medium/long term. In line with the investments made, the evolution of expected emissions over the entire planning horizon also follows a predictable trend. For instance, because of the huge investments in stage 1, the expected (average) emissions are significantly reduced, and a similar phenomenon can be observed in stage 4. Apart from these two stages, emissions tend to slightly increase. Such increase in emissions can be explained by the increasing trend of demand because, in the absence of more investments in RESs, the power generated by non-renewable generators should be increased to meet the increasing demand. However, as illustrated in Fig. 1, the average emissions curve remains far below that of the "do-nothing" scenario, where no investments are assumed to be made.

The practicality of the proposed stochastic model can be shown by comparing decisions made under uncertainty and by ignoring uncertainty. One relevant metric here is the expected cost of ignoring uncertainty (ECIU), which measures the cost of making naïve decisions i.e. assuming that a given scenario happens with certainty. This metric can be alternatively understood as the value of stochastic solution. In the considered system, the ECIU is calculated to be 3.43 M€, which is not negligible. For perspective, one can compare this value with the total NPV of investment costs in the first period in Table III. It can be easily observed that the ECIU amounts to more than 7% of this cost. Moreover, note that this value is a weighted sum of the cost of ignoring uncertainty (CIU) across all scenarios. Depending on which deterministic scenario is taken to obtain the naïve decisions, the CIU value varies tremendously. For some scenarios, it is about 21 M€, which shows that naïve/deterministic solution (i.e. decisions made by ignoring uncertainty) can have significant costs. In other words, this indicates the quality of the stochastic solution, and hence, the practicality of the proposed stochastic model.

TABLE I. 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	0.0584
2	Solar	PV 2	1.5	40	3.83	0.08	0.0584
3	Solar	PV 3	2.0	40	4.55	0.09	0.0584
4	Solar	PV 4	2.5	40	5.20	0.10	0.0584
5	Solar	PV 5	3.0	40	5.80	0.12	0.0584
6	Solar	PV 6	4.0	40	6.89	0.14	0.0584
7	Solar	PV 7	6.0	40	8.79	0.17	0.0584
8	Solar	PV 8	10	40	11.94	0.24	0.0584
9	Wind	WD 1	1.0	17	2.64	0.05	0.0276
10	Wind	WD 2	2.0	17	4.00	0.08	0.0276
11	Wind	WD 3	5.0	17	6.93	0.14	0.0276
12	Wind	WD 4	10	17	10.51	0.21	0.0276
13	CGT**	CGT 1	30	145.4	27.00	0.01	0.5600
14	Biomass	BM 1	20	20	80.00	3.00	0.0900

** *Combustion gas turbine*

TABLE II. Demand Growth and Emission Price Scenarios

	Demand growth scenarios			Emission price scenarios (€/ton of CO_2)		
Stages	Low	Moderate	High	Low	Moderate	High
τ=0	0.0%	0%	0%	7	7	7
τ=1	2.0%	5%	10%	10	35	50
τ=2	5.0%	10%	20%	20	50	100
τ=3	7.0%	15%	30%	30	75	150
ζ=4	9.0%	20%	40%	30	75	150
ζ=5	11.0%	25%	50%	30	75	150
ζ=6	13.0%	30%	60%	30	75	150
ζ=7	14.5%	35%	70%	30	75	150
ζ=8	16.0%	40%	80%	30	75	150

TABLE III. DG INVESTMENT DECISIONS

Horizon	Stages	DG investment solution	NPV of investment cost (M€)
1st period	$\tau = 1$	PV7, PV8, WD1, WD2, WD3, WD4	47.849
	$\tau = 2$	-	0
	$\tau = 3$	-	0
2nd period	$\zeta = 4$	PV6, PV7, PV8, WD1, WD2, WD3, WD4	24.315†
	$\zeta = 5$	PV5, PV6, PV7, PV8, WD1, WD2, WD3	1.566†
	$\zeta = 6$	PV4, PV6, PV7, PV8, WD1, WD2	0.923†
	$\zeta = 7$	PV4, PV5, PV6, PV7, PV8, WD1, WD2	0.776†
	$\zeta = 8$	PV3, PV4, PV5, PV6, PV7, PV8, WD1, WD2	0.880†
NPV of total costs (M€)			470.415

† *Expected investment cost (weighted by the probabilities)*

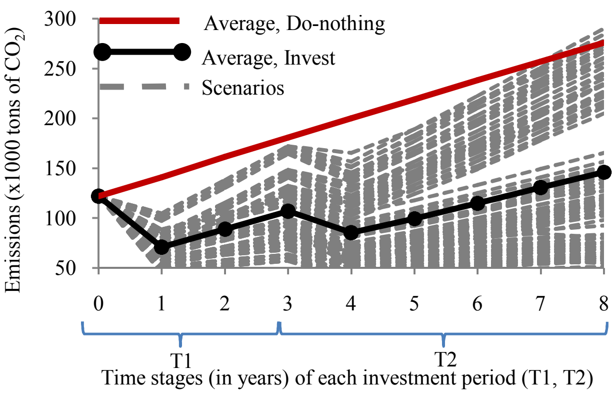

Fig. 1 Evolution of CO_2 emissions over the planning stages

VII. CONCLUSIONS

This paper has presented a new stochastic decision-supporting tool for DG investment planning. The developed model features a number of important aspects. First, the model is formulated as a MILP optimization problem that simultaneously minimizes emission, operation, maintenance and reliability costs. Second, it accounts for the operational variability due to intermittent power sources and electricity demand via probabilistic methods. Moreover, uncertainty related to emission price, demand growth and the unpredictability of intermittent generation sources is handled via a stochastic approach. Third, it is based on a dynamic decision framework i.e. involving a multi-year decision structure. Another salient feature of the model is that it is based on a two-period planning framework, involving a short-term and a medium/long-term planning windows. This helps one to obtain robust short-term decisions in the face of uncertainty along with strategic (or flexible) decisions in the medium to long-term planning horizon. The developed model has been tested on a real-life DN system, and the results of the analyses have generally shown the effectiveness of the proposed model. Compared to deterministic or naïve decisions, the stochastic model proposed here yields better and more robust decisions.

ACKNOWLEDGMENT

This work was supported by FEDER funds through COMPETE and by Portuguese funds through FCT, under Projects FCOMP-01-0124-FEDER-020282 (Ref. PTDC/EEA-EEL/118519/2010) and UID/CEC/50021/2013, and also by funds from the EU 7th Framework Program FP7/2007-2013 under grant agreement no. 309048.

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] 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.

[3] 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.

[4] 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.

[5] 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.

[6] 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.

[7] 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.

[8] 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.

[9] 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.

[10] 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.

[11] 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.

[12] F. Katiraei and J. R. Agüero, "Solar PV Integration Challenges," *IEEE Power Energy Mag.*, vol. 9, no. 3, pp. 62–71, May 2011.

[13] 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.

[14] M. Shivaie, M. T. Ameli, M. S. Sepasian, P. D. Weinsier, and V. Vahidinasab, "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.

[15] G. Muñoz-Delgado, J. Contreras, and J. M. Arroyo, "Joint Expansion Planning of Distributed Generation and Distribution Networks," *IEEE Trans. Power Syst.*, vol. PP, no. 99, pp. 1–12, 2014.

[16] 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.

[17] 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.

[18] 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.

[19] 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.

[20] 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.

[21] 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.

[22] M. Ahmadigorji and N. Amjady, "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.

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

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

[25] 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.

[26] D. Z. Fitiwi, 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.