Optimal Expansion Planning Considering Storage Investment and Seasonal Effect of Demand and Renewable Generation

Bruno Canizes¹, João Soares¹, Fernando Lezama¹, Cátia Silva¹, Zita Vale¹,
Juan M. Corchado^{2,3,4}

¹*GECAD - Knowledge Engineering and Decision Support Research Center - Polytechnic of Porto (IPP), R. Dr. António Bernardino de Almeida, 431, 4200-072 Porto, Portugal*

²*University of Salamanca, 37008 Salamanca, Spain*

³*Osaka Institute of Technology, 5 Chome-16-1 Omiya, Asahi Ward, Osaka, Japan*

⁴*University of Technology Malaysia, Pusat Pentadbiran Universiti Teknologi Malaysia, 81310 Skudai, Johor, Malaysia*

Abstract

A new era of cleaner distributed generators, like wind and solar, dispersed along the distribution network are gaining great importance and contributing to the environment and political goals. However, the variability and intermittency of those generators pose new complexities and challenges to the network planning. This research paper proposes an innovative stochastic methodology to deal with the expansion planning of large distribution networks in a smart grid context with high penetration of distributed renewable energy sources and considering the seasonal impact. Also, new power lines locations and types, the size and the location of energy storage systems are considered in the optimization. A distribution network with 180 buses located in Portugal considering high distributed generators penetration is used to illustrate the application of the proposed methodology. The results demonstrate the advantage of the stochastic model when compared with a deterministic formulation, avoiding the need for larger investments in new lines and energy storage systems.

Keywords: Distribution networks; energy storage systems; planning; renewable energy sources; smart grid; stochastic systems.

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1. Introduction

The increasing energy needs are mostly satisfied by non-renewable energy sources like coal or natural gas. However, these energy resources are scarce and can bring negative consequences to the environment. The growing load trend in distribution networks (DN) requires through planning an upgrade of the network. This growth can be related to the consumers' new requirements, for instance an increase of the electrical based home equipment and the number of electrical vehicles. Furthermore, several innovative developments in power distribution systems have taken place around the world. One of them is related to the minimization of the carbon footprint using a large-scale integration of renewable energy sources (RES) such as wind and solar. Due to this, the European Union (EU) has set the target of achieving 20% of RES in the final energy consumption by 2020. Furthermore, to meet the energy requirements beyond 2020, a new agreement in the EU aims at a target of 27% of RES penetration by 2030 [1]. Moreover, *The European Union Leading in Renewables* document [2] states that one-third of EU countries has already achieved the 2020 target.

Despite the need of high penetration of RES to meet EU targets and address environmental issues, the distributed generators based on renewable sources (solar and wind) carry an inherent variability that introduces several economic and technical challenges to distribution network planner. This unpredictability should be managed efficiently by smart grid (SG) technologies to accommodate high penetration of RES. But in several countries, it is just common to expand or reinforce the grid. Moreover, the actual DN design is not fully prepared to integrate a large number of distributed RES units. The normal operation of the DN can be affected positively or negatively by the high penetration of this kind of generators [3–6]. Thus, several works related to planning and operation of distribution network with distributed generation (DG) penetration have been published in specialized literature [7–13]. [7] proposes a two-stage stochastic model for large-scale energy resources scheduling problem of aggregators in a SG considering the variability of demand, renewable energy, EVs, and market price variations while minimizing the total operation cost. Benders' decomposition approach is used to improve the tractability of the model and its' computational burden. Choi et al. [8] propose a probabilistic expansion technique for transmission systems to minimize the new lines construction cost. A method that combines optimization and probabilistic analysis to maximize the number of wind turbines

52 subject to the voltage stability limits, thermal limits, voltage limits, load tap
 53 changing and generator power output limits is proposed in [9]. [10] presents
 54 a work to minimize the system power losses by controlling the power factors
 55 of wind turbine. The optimization problem is constrained by the bus volt-
 56 age and line current requirements and use the stochastic wind power model
 57 generation and load demand to consider the stochastic variation. Reference
 58 [11] presents a method for smart grid management that minimizes the to-
 59 tal cost to deliver energy to consumers (distributed generation costs, costs
 60 from the power provided by the primary substation, and the power losses).
 61 Hengsritawat et al. [12] propose a probabilistic approach to design the PV
 62 optimal size to be used in distribution networks and the location of the PV
 63 by using a steady-state voltage stability index while minimizing the average
 64 system power losses. [13] proposes a long-term distribution network plan-
 65 ning under urbanity uncertainties to eliminate the harmful effects. At the
 66 end, the network is designed through branch exchange method which con-
 67 sider the embranchment points as representative to load points. Reference
 68 [14] presents a new state reduction algorithm for DG planning problems and
 69 reliability analysis by determining the minimum number of states required
 70 to represent the wind speed and solar irradiance behavior. Hemmati et al
 71 [15] proposes a multistage electricity generation expansion planning in order
 72 to minimize the planning cost and environmental pollution incorporating
 73 largescale energy storage systems. The problem is solved by a PSO algo-
 74 rithm. [16] proposes a long-term dynamic multi-objective planning model
 75 for distribution network expansion where two objectives are minimized, i.e.,
 76 costs and emissions. The model can also determine the optimal sizing and
 77 placement and the dynamics of investments on distributed generation units
 78 and network reinforcements over the planning period. To deal with this prob-
 79 lem a two-stage heuristic method is used. A distribution network multiyear
 80 expansion planning is proposed in [17]. The model includes the primary feed-
 81 ers reinforcement as well as the location and size of DG. A binary chaotic
 82 shark smell optimization is used to solve the problem. Asensio et al. [18] pro-
 83 pose a bi-level model under a demand response framework for a distribution
 84 network and renewable energy expansion planning. Two problem levels are
 85 considered, an upper-level to minimize generation and network investment
 86 cost while meeting the demand and a lower level to minimize the overall
 87 payment faced by the consumers. The problem is a mixed integer linear pro-
 88 gramming (MILP) using the Karush Kuhn Tucker (KKT) complementarity
 89 constraints and is solved by branch-and-cut solvers. [19] presents a stochastic

two-stage multiperiod MILP model for the optimal allocation and timing of renewable distributed generation under uncertainty. The goal is to minimize renewable distributed generation investment costs, substation expansion investment cost, operation and maintenance costs, power losses cost, and the costs of the power purchased from the transmission system. [20–22] propose models for joint distribution network expansion and distributed generation planning using a multi-stage stochastic linear programming. Mokryani et al. [1] present an approach for distribution networks planning within a distribution market environment considering multi-configuration of wind turbines and PV. A multi-configuration and multi-period market-based optimal power flow are used to maximize the social welfare considering the uncertainties associated with wind speed, solar irradiance and load demand.

The above-cited literature has not addressed the long-term distribution network expansion planning problem with high RES penetration concerning the daily and seasonal variability, the selection of the size and location of energy storage systems (ESS) as well as the location and types of new power lines. This problem has not been solved yet in the literature to the best of authors' knowledge. Thus, the present research paper proposes an innovative stochastic MILP methodology based on DC optimal power flow to deal with the expansion planning, in only one period of investment (year 0), of large medium voltage (MV) distribution networks with high penetration of renewable energy sources considering the seasonal impact identifying at the same time new power lines locations and types, the size and the location of ESS. The main target is to minimize all the expenditures. For this, the proposed methodology seeks:

- Improve the network reliability through the expected not supplied energy minimization;
- Minimize the power losses;
- Minimize the power generation curtailment (PGC);
- Minimize load curtailment;
- Minimize all investment costs;
- Optimal type and location for new lines;
- Optimal ESS size and location;

- Distribution network Radial topology.

The DC optimal power flow is used to reduce the complexity and computational burden of the model, improving its tractability. As a consequence, the voltage magnitude is one p.u. and the reactive power flow is neglected. On the other hand, MV distribution networks in several countries like Portugal have transformer with automatic voltage regulators and capacitor banks carefully placed along the network to keep the voltage and reactive power between the desired limits. Thus, using a complete model for the long-term planning problem (i.e., AC optimal power flow) would only make the method more complex and computationally heavy. This methodology considers the typical annual demand profile for the considered network region taking into account the projected change by *EU Reference Scenario 2016: Energy, Transport and GHG emissions trends to 2050* [23] for Portugal in 2050 as well as the number of consumers forecast for the region in 2050 according to *Statistic Portugal* [24].

Comparing with the previous works, this paper presents the following major contributions:

1. Considering the seasonal (spring, summer, fall and winter) and daily periods (night, morning, peak and afternoon) impact effect in a long-term distribution network planning in a SG context with high RES penetration;
2. Presenting the optimal ESS size and location as well as the optimal type and location of new lines or the replacement of the existent ones per other types under the previous point conditions. At the same time the reliability improvement and the network radial topology are sought.

To demonstrate the application of the proposed methodology, a part of distribution network with 180 buses located at Leiria District in Portugal considering high RES penetration (with defined locations) is used. As a base case, the proposed stochastic method is applied to the actual network without any investment alternatives, i.e., without new lines possibility and ESS. In addition, a comparison between the stochastic model and the deterministic model was undertaken to show how much improvement can be achieved by our stochastic solution.

This paper is organized as follows: after this introduction, Section 2 presents the proposed methodology and the details information about the

158 stochastic and deterministic approaches, uncertainty data, scenarios creation,
159 optimization model and economic analysis. The case study to show the ap-
160 plication of the proposed methodology is shown in Section 3. The results
161 and its discussion are presented in Section 4. Finally, Section 5 presents the
162 most relevant conclusions.

163 **2. Proposed methodology**

164 This section presents the adopted methodology used in this work. Sub-
165 section 2.1 shows details about the stochastic and deterministic approaches,
166 as well as about the uncertainty data. Subsection 2.2 presents the method
167 for developing the renewable energy resources scenarios, such as wind and
168 solar power, as well as the load demand projections. The proposed two-stage
169 stochastic optimization model is presented in subsection 2.3. Finally, a briefly
170 description of the adopted economic analysis is presented in sub-section 2.4.

171 *2.1. Stochastic and deterministic models*

172 The expansion planning problem is formulated in this section as a two-
173 stage stochastic model and a deterministic model. Theoretical background
174 on two-stage or multi-stage stochastic programming models can be found in
175 [25]. The idea is to make an optimal decision in the first stage ("here-and-now
176 decisions"), on the lines and storage systems investments and maintenance,
177 while considering the uncertainties of wind generation, PV generation and
178 load demand in the second stage ("wait-and-see decisions"). In the first
179 stage, the decisions are made before the realization of the stochastic process.
180 Hence, variables representing here-and-now decisions do not depend on each
181 realization of the stochastic process [26]. In the second stage, the decisions
182 are made after knowing the actual realization of the stochastic process. Con-
183 sequently, these decisions depend on each realization vector of the stochastic
184 process. If a set of scenarios represents the stochastic process, a second stage
185 decision variable is defined for every single scenario considered [26]. In other
186 words, the first-stage decisions of the stochastic model must fit and satisfy
187 the constraints for every scenario, i.e., the variables without uncertainty do
188 not change across the several scenarios. The goal is to minimize all the
189 expenditures costs. With the proposed model, it is possible to obtain the
190 improvement of the network reliability, the reduction of power losses, power
191 generation curtailment, load curtailment, the optimal location for new lines
192 and the optimal ESS size and location while the radial topology is ensured.

193 To achieve this, a scenario-based approach is used to model the underlying
 194 uncertainty. It means that wind and solar generation, or the load demand,
 195 varies from one scenario to another.

196
 197 For the deterministic model, the average scenario of distributed gener-
 198 ation power and the projected power demand are modelled following the
 199 equations (1) and (2) respectively:

$$\sum_{s \in \Omega_s} p_{DG(i,s)} \cdot prob_{(s)} \quad \forall i \in \Omega_{DG}^{nd} \quad (1)$$

$$\sum_{s \in \Omega_s} p_{Load(i,s)} \cdot prob_{(s)} \quad \forall i \in \Omega_L^b \quad (2)$$

200 Thus, the average scenario for wind/PV generation is modelled by the
 201 summation of generated power in each scenario multiplied by the correspon-
 202 dent scenario probability (1). Also, the average scenario for the projected
 203 load is modelled by the summation of load demand in each scenario multi-
 204 plied by correspondent scenario probability (2).

205 2.1.1. Uncertain data

206 In stochastic programming problems, the stochastic processes are repre-
 207 sented by continuous or discrete random variables. Dealing with a finite set
 208 of possible outcomes is the adopted way in decision-making problems under
 209 uncertainty; otherwise it would be impossible to solve the problem [26–28].
 210 An appropriate representation of a continuous random variable using a finite
 211 set of values can be difficult. Scenarios can be generated using different tech-
 212 niques, including path-based methods, moment matching, internal sampling
 213 and scenario reduction [26]. Different realizations of the random variables
 214 can be represented by arcs in a scenario tree. The probability of a scenario to
 215 occur is the product of the probabilities associated with the arcs. The sum
 216 of the probabilities of the generated scenarios is equal to 1. Figure 1 presents
 217 a simple example of one scenario tree with five scenarios and ten nodes. A
 218 scenario tree represents the abstract structure of scenarios. It shows how
 219 the uncertainty unfolds over time. Each complete path from the root node
 220 $n1$ to one of the leaves $n6, \dots, n10$ represents a scenario. For instance, sce-
 221 nario 1 ($n6$) results from the product of nodes $n2, n3$. Stochastic processes

222 approximations in the form of scenario trees are useful for the formulation
 223 of multiperiod dynamic decision models as multistage stochastic programs.
 224 A multistage stochastic programming model will determine an optimal de-
 225 cision for each node of the scenario tree, given the information available at
 226 that point. As there are multiple succeeding nodes, the optimal decisions
 227 will not exploit hindsight, but they should anticipate future events [29].

Figure 1: Scenario tree with 5 scenarios [29]

228 2.2. Projected scenarios

229 In this sub-section, the method to determine the probability of each con-
 230 sidered scenario is presented. A consistent database of radiation, temperature
 231 and wind measurements of the region where the PVs and wind generators
 232 shall be installed is needed to create the scenarios described in this methodol-
 233 ogy. In this work, the authors considered a set of 16 scenarios corresponding
 234 to the combination of the four annual seasons (i.e., spring, summer, fall, and
 235 winter) and four daily periods (i.e., night, morning, peak and afternoon).
 236 Figure 2 shows all the considered 16 scenarios.

Figure 2: Probability tree diagram for a set of 16 scenarios, where SP represents the scenario probability, NT - Night, MO - Morning, PK - Peak and AF - Afternoon

The method is dependent on the characteristics of the region considered. The number of days in each season where the methodology is applied as well as the number of hours in each daily period are needed to determine the probability of each scenario. Let's take the example for a night in the spring season scenario:

- Spring season days: 92 days;
- Daily period: night;
- Number of hours in night period: 12 hours (from 20h to 7h).

Taking into account the number of hours in a year (i.e., 8760 hours), it is possible to determine the scenario probability (3).¹

$$SP1 = \frac{92 \times 12}{8760} = 0.1260 \rightarrow 12.60\% \quad (3)$$

With the adequate historical data (load demand, renewable generation), it is possible to associate possible projections for the night period (spring) to the probability SP1, which in this case is 12.60%.

¹In section 3, the reader can found a scenario tree diagram (figure 7) with the probabilities used in this study.

251 The PV module output power depends on the solar radiation, tempera-
 252 ture and its characteristics and can be calculated by (4)-(8) [30]:

$$T_{cell} = T_{Amb} + A_{sr} \cdot \left(\frac{N_{OP} - 20}{0.8} \right) \quad (4)$$

$$I_{PV} = A_{sr} \cdot (I_{SC} + T_I \cdot (T_{cell} - 25)) \quad (5)$$

$$V_{PV} = V_{OP} - T_V \cdot T_{cell} \quad (6)$$

$$F_F = \frac{V_M \cdot I_M}{V_{OP} \cdot I_{SC}} \quad (7)$$

$$P_{cell} = N_m \cdot T_V \cdot F_F \cdot V_{PV} \cdot I_{PV} \quad (8)$$

Regarding to wind power, it can be calculate by (9) [30]:

$$P_w = \begin{cases} 0 & 0 \leq v_w \leq v_{ci} \\ P_{rated} \cdot \frac{(v_w - v_{ci})}{(v_{co} - v_{ci})} & v_{ci} \leq v_w \leq v_r \\ P_{rated} & v_r \leq v_w \leq v_{co} \\ 0 & v_r \leq v_{co} \end{cases} \quad (9)$$

253 As alternative, wind power can be determined through the power curve
 254 given by the wind generators manufacturer.

255 Figure 3 presents a diagram that illustrates the scenarios created for re-
 256 newable generation and power demand. After the scenarios probability de-
 257 termination, the expected wind power and PV power, as well as the projected
 258 power demand for each combination of four annual seasons and four daily
 259 periods, are multiplied by the respective probability.

Figure 3: Scenarios diagram creation.

Furthermore, the next five steps summarize how to obtain the probability of each scenario.

Step 1: A real hourly database regarding wind speed, solar irradiance, temperature and demand was considered;

Step 2: The data must be arranged by seasons (spring, summer, fall and winter) and daily periods (night, morning, peak and afternoon);

Step 3: each season and daily periods values, the PV generation power is calculated using equation (4)-(8), the Wind power by (9) or in alternative using the power curve given by the wind generators manufacturer. The PV and wind generators units' types and locations are already previously defined in the distribution network. For the load demand it is considered the typical annual demand profile for the considered network region taking into account the projected change by *EU Reference Scenario 2016: Energy, Transport and GHG emissions trends to 2050* [23] for Portugal in 2050;

Step 4: After the previous step, the mean value of each season and daily period is obtained;

Step 5: The probabilities of each scenario (each daily period in each season) are obtained following the method used in the example shown in this subsection;

Step 6: After steps 4 and 5, it is possible to determine the probabilities of projected wind power, projected PV power, and projected demand for each daily period in each season.

2.3. Optimization model

This sub-section presents the two-stage stochastic optimization model developed in this work. In the Figure 4 is represented the model structure indicating which variables are from the first and second stage.

Figure 4: Structure of the adopted two-stage stochastic optimization model.

289 The optimization model presents the following outputs variables²:

- 290 • New lines and feeders types and their locations;
- 291 • New lines investment cost and feeders investment cost (including trans-
292 former cost);
- 293 • Location of ESS and its type;
- 294 • Energy storage systems investment cost;
- 295 • Power losses and its cost;
- 296 • Expected energy not supplied value and its cost;
- 297 • Power generation curtailment value and its cost;
- 298 • Optimal radial topology;
- 299 • Power flow;
- 300 • Reliability system indexes, as the System Average Interruption Fre-
301 quency Index (SAIFI) and System Average Interruption Duration In-
302 dex (SAIDI).

303 Equation (10) presents the total expected planning cost, which includes
304 the new lines and feeders investment cost, the maintenance cost of all lines,
305 the investment in ESSs and their maintenance cost which corresponds to the
306 first-stage (PC_1 - equation (11)). This equation also includes a second-stage
307 (PC_2 - equation (12)) corresponding to the costs associated with the ex-
308 pected energy not supplied, power losses, power generation curtailment and
309 load curtailment.

310
311 Objective function

$$\text{Minimize } PC = PC_1 + PC_2 \quad (10)$$

---

²The full nomenclature used in the optimization model is provided in the corresponded section at the end of this paper.

$$PC_1 = \left[\begin{array}{l} \sum_{i \in \Omega_B} \sum_{j \in \Omega_B} \sum_{c \in \Omega_O} y_{(i,j,c)} \cdot LineCost_{(i,j,c)} + \\ \sum_{i \in \Omega_B} \sum_{j \in \Omega_B} \sum_{c \in \Omega_O} y_{(i,j,c)} \cdot LineMCost_{(i,j,c)} + \\ \sum_{u \in \Omega_{STO}} a_{(e,u)} \cdot StCost_u + \\ \sum_{u \in \Omega_{STO}} a_{(e,u)} \cdot StMCost_u \end{array} \right] \quad (11)$$

312

313

$$PC_2 = \sum_{s \in \Omega_s} \left[\begin{array}{l} \left(\sum_{i \in \Omega_B} \sum_{c \in \Omega_O} Flow_{(i,j,c,s)} \cdot FOR_{(i,j,c)} \right) \cdot ENSCost + \\ \left(\sum_{i \in \Omega_B} \sum_{c \in \Omega_O} Flow_{(i,j,c,s)} \cdot LF_{(i,j,c)} \right) \cdot LossC + \\ \sum_{g \in \Omega_{DG}^{nd}} P_{PGC(g,s)} \cdot PCost_{PGC(g)} + \\ \left(\sum_{lo \in \Omega_L^b} p_{LoadCut(lo,s)} \cdot CutCost_{lo} \right) \end{array} \right] \cdot \omega_s \quad (12)$$

314 Forced outage rate (FOR) is determined taking into account the basics
 315 reliability indexes r and λ used to calculate the remaining indicators (SAIFI,
 316 SAIDI, expected energy not supplied (EENS)). Thus, once the FOR is min-
 317 imized, those indicators are minimized as well.

318

where:

$$FOR_{(i,j,c)} = \frac{U_{(i,j,c)}}{8760 - r_{(i,j,c)}} = \frac{\lambda_{(i,j,c)} \cdot r_{(i,j,c)}}{8760 - r_{(i,j,c)}} \quad (13)$$

319

320

321

322 $FOR_{(i,j,c)}$ - is the forced outage rate between bus i and bus j according
 323 to the chosen line option c

324

325 $U_{(i,j,c)}$ - is the unavailability between bus i and bus j according to the
 326 chosen line option c [hours/year]

327

328 $r_{(i,j,c)}$ - is the repair time between bus i and bus j according to the chosen
 329 line option c [hours]

330

331 $\lambda_{(i,j,c)}$ - is the failure rate between bus i and bus j according to the chosen
 332 line option c [failures/year]

333

334 $ENSCost$ - is the fixed energy not supplied cost defined by the regulator
 335 entity [€/MWh]

336

337 $LF_{(i,j,c)}$ - is the loss factor between bus i and bus j according to the cho-
 338 sen line option c

339

340 $LossC$ - is the fixed power losses cost defined by the regulator entity
 341 [€/MWh]

342

343

344 Since the power loss is a quadratic function, (12) is a nonlinear function.
 345 Thus, to make (12) linear, it is necessary to linearize the power losses. This
 346 linearization can be done, for instance, through the Venikov method (14)
 347 [31, 32]. This method assumes that the system components (for instance,
 348 lines and cables) are design to operate near to the nominal current.

$$\Delta p_{(i,j,c,s)} \simeq Flow_{(i,j,c,s)} \cdot LF_{(i,j,c)} \quad (14)$$

349 LF is usually called Loss Factor and is defined as follows (16):

$$LF_{(i,j,c)} = \frac{k_{(i,j,c)} \cdot \rho_{(i,j,c)} \cdot L_{(i,j,c)} \cdot J_{eco(i,j,c)}}{V_i} \quad (15)$$

350

351 where:

$$J_{eco(i,j,c)} \simeq \frac{I_{(i,j,c)}}{S_{ec(i,j,c)}} \quad (16)$$

$J_{eco(i,j,c)}$ - Current density between bus i and bus j according to the chosen line option c [A/mm²]

$S_{ec(i,j,c)}$ - Line section between bus i and bus j according to the chosen line option c [mm²]

352 $k_{(i,j,c)}$ - Constant that depends on the type of service (one or three phases)
353 between bus i and bus j according to the chosen line option c

354

355 $I_{(i,j,c)}$ - Nominal current between bus i and bus j according to the chosen
356 line option c [A]

357

$\rho_{(i,j,c)}$ - Line resistivity at operating temperature between bus i and bus j according to the chosen line option c [$\Omega \cdot mm^2/km$]

358 $L_{(i,j,c)}$ - Line length between bus i and bus j according to the chosen line
359 option c [km]

360

361 $V_{(i)}$ - Voltage in bus i (in DC model the voltage value is considered 1 *p.u.*
362 for all buses)

363

364 Objective function (10) is subjected to constraints (17)-(39).

365

366 **Network constraints**

367

368 Power balance - first Kirchhoff law

369

370 The amount of generated power should be equal to the demand. Multi-
371 scenario balance must be satisfied for all different scenarios s . The stochastic
372 model has a much higher number of energy balance constraints than the de-
373 terministic counterpart. The equation terms include the renewable genera-
374 tion, the power acquisition to substation/external supplier, the load demand,

375 power generation curtailment, load curtailment, EV parking lots charge, lines
 376 power flow and ESS charge/discharge. The result of this equation as repre-
 377 sented should be zero. The stochastic balance constraint will validate if the
 378 first stage variables can match the balance among the different scenarios s
 379 as follows (17):

$$\begin{aligned}
 & \sum_{i \in \Omega_{DG}^{nd}} (p_{DG(i,s)} - p_{PGC(i,s)}) + \sum_{i \in \Omega_{BS}^b} p_{Supplier(i)} + \\
 & \sum_{i \in \Omega_L^b} p_{LoadCut(i,s)} - \sum_{i \in \Omega_L^b} p_{Load(i,s)} - \sum_{i \in \Omega_E^b} \sum_{u \in \Omega_E} P_{storage(i,u,s)} - \\
 & \sum_{i \in \Omega_V^b} EV P(i) - \sum_{i \in \Omega_B} \sum_{c \in \Omega_O} (Flow_{(i,j,c,s)} \cdot LF_{(i,j,c)}) + \sum_{i \in \Omega_B} \sum_{c \in \Omega_O} Flow_{(i,j,c,s)} - \\
 & \sum_{i \in \Omega_B} \sum_{c \in \Omega_O} Flow_{(j,i,c,s)} = 0 \quad \forall s \in \Omega_s, \forall j \in \Omega_B
 \end{aligned} \tag{17}$$

380

381 Maximum admissible line flow

382

The maximum power flowing in each line is guaranteed by (18).

$$\begin{aligned}
 0 & \leq Flow_{(i,j,c,s)} \leq Flow_{(i,j,c)}^{\max} \cdot y_{(i,j,c)} \quad \forall s \in \Omega_s, \forall y \in \{0, 1\}, \\
 & \forall (i, j, c) \in \Omega_l
 \end{aligned} \tag{18}$$

383

384 Unidirectionality of power flow

385

Constraint (19) guarantees unidirectionality between bus i and j and also the choice of only one line type c in that direction.

$$y_{(i,j,c)} + y_{(j,i,c)} \leq 1 \quad \forall y \in \{0, 1\}, \forall (i, j, c) \in \Omega_l \tag{19}$$

386

387

388

389

390 One line type

391

Only one line type c can be chosen for each line location.

$$\sum_{c \in \Omega_O} y_{(i,j,c)} \leq 1 \quad \forall y \in \{0, 1\}, \forall (i, j, c) \in \Omega_l \quad (20)$$

392

393

394 Radial topology

395

To ensure the radial topology, constraint (21) is applied. This constraint imposes that only one line can enter in each bus.

$$\sum_{j \in \Omega_L^b} \sum_{c \in \Omega_O} y_{(i,j,c)} = 1 \quad y \in \{0, 1\}, \quad \forall i \in \Omega_B \quad (21)$$

396

397

398 Avoid island creation

399

400 To avoid DG isolation from the substation, the constraints (22)-(25) are
 401 applied to the mathematical model. To do this, it is created a fictitious flow
 402 ($d_{(i,j,c)}$) with a fictitious load of each DG ($D_{(g)}$) to be fed by the substation.
 403 If the island is permitted, the planner can omit these equations.

$$\sum_{i \in \Omega_B} \sum_{j \in \Omega_B} \sum_{c \in \Omega_O} d_{(i,j,c)} - \sum_{i \in \Omega_B} \sum_{j \in \Omega_B} \sum_{c \in \Omega_O} d_{(j,i,c)} = D_{(g)} \quad (22)$$

$$\forall g \in \Omega_{DG}$$

$$D_{(g)} = 1 \quad \forall g \in \Omega_{DG} \quad (23)$$

$$D_{(g)} = 0 \quad \forall g \notin \Omega_{DG} \cup \Omega_{BS} \quad (24)$$

$$|d_{(i,j,c)}| \leq n_{DG} \cdot y_{(i,j,c)} \quad \forall (i, j, c) \in \Omega_l \quad (25)$$

Substation constraint

Maximum and minimum limits for substation supplied power

The power supplied by substation is constrained by the maximum and minimum capacity that can supply.

$$P_{SMinLimit}(bs) \leq p_{Supplier}(bs) \leq P_{SMaxLimit}(bs) \quad \forall bs \in \Omega_{BS} \quad (26)$$

Energy storage systems constraints

Charge considering energy storage systems capacity

The maximum charge limit considering energy storage systems capacity constraint for each ESS is given by (27).

$$p_{storage(e,u,s)} \leq \frac{stCap_{(e,u)}}{cef \cdot \Delta t_{(s)}} \quad \forall e \in \Omega_E^b, \forall u \in \Omega_E, \forall s \in \Omega_S \quad (27)$$

Discharge considering energy storage systems capacity

The maximum discharge limit considering energy storage systems capacity constraint for each ESS is given by (28).

$$p_{storage(e,u,s)} \geq \frac{-stCap_{(e,u)}}{def \cdot \Delta t_{(s)}} \quad \forall e \in \Omega_E^b, \forall u \in \Omega_E, \forall s \in \Omega_S \quad (28)$$

Constraints (27) and (28) represent an approximation of the real ESS usage after deployment. Since each scenario represents more than one hour (e.g., night summer hours), it would be unrealistic to consider that a battery could charge/discharge at maximum power during the represented season. A more realistic method would be to consider each hour as a scenario, i.e., representing one hour of the year (8760 scenarios) and considering the state

of the charge of the ESS in each hour. However, such realistic method would imply a substantial computational burden, leading to an intractable formulation. Thus, it was considered that the maximum ESS power can charge and discharge is $\frac{stCap_{(e,u)}}{cef \cdot \Delta t_{(s)}}$ and $\frac{-stCap_{(e,u)}}{def \cdot \Delta t_{(s)}}$, respectively.

Charge rate limit

$$\begin{aligned} p_{storage_{(e,u,s)}} &\leq stRate_{(e,u)} \cdot a_{(e,u)} & \forall a \in \{0, 1\}, \forall e \in \Omega_E^b, \\ & & (29) \\ \forall u \in \Omega_E, \forall s \in \Omega_S \end{aligned}$$

Discharge rate limit

$$\begin{aligned} p_{storage_{(e,u,s)}} &\geq -stRate_{(e,u)} \cdot a_{(e,u)} & \forall a \in \{0, 1\}, \forall e \in \Omega_E^b, \\ & & (30) \\ \forall u \in \Omega_E, \forall s \in \Omega_S \end{aligned}$$

Constraints (29) and (30) present the ESS charge and discharge rate limits, respectively. $a_{(e,u)}$ is a binary decision variable, which is 1 when the u type ESS is chosen to be placed in bus e .

One ESS type

Only one ESS type (u) can be chosen for each selected bus location.

$$\sum_{u \in \Omega_E} a_{(e,u)} \leq 1 \quad \forall a \in \{0, 1\}, \forall e \in \Omega_E^b \quad (31)$$

441

442 **Parking lots constraint**

443

444 Parking lots constraint

445

In this model, the EVs are considered as parking lots or a set of EVs located in the network. The parking lot charge is equal to charge limit multiplied by simultaneity factor (sf). The charge limit for each parking lot v is represented by (32).

$$PCharge_{(v,s)} = PChargeLimit_{(v,s)} \cdot sf_v \quad \forall v \in \Omega_V^b, \forall s \in \Omega_S \quad (32)$$

446

447

448 **Reliability indexes**

449

The assessment of reliability indexes, like System Average Interruption Frequency Index (SAIFI) and System Average Interruption Duration Index (SAIDI), is an important issue to be considered in distribution network planning. Thus, in the proposed methodology, the network planner can define desired target values for SAIFI and SAIDI. The definition of those two indexes follows the equations (33)-(36).

$$SAIFI = \frac{\text{Total number of customers interruptions}}{\text{Total number of costumers in the system}} \quad (33)$$

$$SAIFI = \frac{\sum_{i \in \Omega_L^b} \lambda p_{(i)} \cdot N_{(i)}}{\sum_{i \in \Omega_L^b} N_{(i)}} \quad \text{interruptions/customer} \cdot \text{year} \quad (34)$$

$$SAIDI = \frac{\text{Total customers interruption durations}}{\text{Total number of costumers in the system}} \quad (35)$$

$$SAIDI = \frac{\sum_{i \in \Omega_L^b} Up_{(i)} \cdot N_{(i)}}{\sum_{i \in \Omega_L^b} N_{(i)}} \quad \text{hour/customer} \cdot \text{year} \quad (36)$$

where:

$\lambda p_{(i)}$ - Is the summation of all lines unavailability (at the view point of load bus i) who represents the path between the load bus and the substation/external supplier bus, i.e., for all lines between load bus and substation/external supplier bus.

$Up_{(i)}$ - Is the summation of all lines failure rate (at the view point of load bus i) who represents the path between the load bus and the substation/external supplier bus, i.e., for all lines between load bus and substation/external supplier bus.

$N_{(i)}$ - Is the number of consumers in bus i .

System Average Interruption Frequency Index

The model is able to impose an improvement of SAIFI by the definition of a desired value of this index.

$$0 \leq SAIFI \leq SAIFI^{\max} \quad (37)$$

System Average Interruption Duration Index

The model can also impose the improvement of SAIDI by defining a desired value for this index.

$$0 \leq SAIDI \leq SAIDI^{\max} \quad (38)$$

Curtailment constraints

Power generation curtailment

The power generation curtailment is verified when the excess of generation of generator g in scenario s occurs. This variable is lower or equal to the

generation of g generator (39).

$$0 \leq p_{GCP(g,s)} \leq P_{DGScenario(g,s)} \quad \forall g \in \Omega_{DG}^{nd}, \forall s \in \Omega_S \quad (39)$$

477

478

479 Load curtailment power

480

Constraint (40) guarantees that load curtailment variable must be lower or equal to the load of the projected scenarios.

$$0 \leq p_{LoadCut(lo,s)} \leq P_{Load(lo,s)} \quad \forall lo \in \Omega_L^b, \forall s \in \Omega_S \quad (40)$$

481

482

483 2.4. Economic analysis

484 All monetary benefits resulted from the investments associated to the
 485 network expansion planning namely new lines and ESS construction, as well
 486 as all expenditures costs related to the network operation (power losses, ex-
 487 pected energy not supplied, power generation curtailment, load curtailment
 488 and lines and ESS maintenance), are considered in the economic analysis.
 489 The project will be profitable when the net present value (NPV) is positive,
 490 i.e., all the monetary benefits (savings) are higher than the total project
 491 lifetime investment (41) [33].

$$\begin{aligned} NPV &= Savings - Investment \\ NPV &> 0 \end{aligned} \quad (41)$$

492 3. Case study

493 A realistic distribution network, which is a part of the distribution net-
 494 work located in Leiria district in Portugal in a deregulated system (the non-
 495 monopolized Portuguese case, where the DSO is responsible only for distri-
 496 bution network planning and operation), is used to show how the proposed
 497 methodology is applied. 0.05% of discount rate [34] is considered for a thirty-
 498 year project lifetime, leading to 0.034 ratio of capital recovery factor (CRF).
 499 Three different cases are considered in this work:

- 500 1. The proposed stochastic model applied to the actual network without
501 any investment alternatives, i.e., without new lines and ESS invest-
502 ment. The purpose is to establish a reference case considering only the
503 minimization costs of power losses, EENS, power generation curtail-
504 ment, and load curtailment;
- 505 2. The proposed stochastic model applied to the actual network with in-
506 vestment alternatives, i.e., new lines and ESS investment options. The
507 objective is to minimize the costs associated with the expected energy
508 not supplied, power losses, power generation curtailment and load cur-
509 tailment. Moreover, the investment costs in new lines and feeders, the
510 maintenance cost of all lines, the investment in ESSs and their main-
511 tenance cost are also minimized;
- 512 3. The deterministic model applied to the actual network with investment
513 alternatives, i.e., new lines and ESS investment options. The goal is
514 to demonstrate performance of the proposed stochastic method when
515 compared with a traditional one (deterministic). The average scenario
516 is calculated and used in the deterministic method.

517 In addition, different values of PGC cost for RES were taken into account.
518 In many countries, the PGC of renewable sources, such wind and solar power,
519 is imposed as a penalty to network operator that represents a compensation
520 for the producers. This compensation varies from country to country. For
521 instance, in the Portuguese case, this compensation is applied only to wind
522 energy. The compensation is equal to the value of the support scheme [35]
523 (for Portugal is the feed-in tariff) with an actual value of 95€/MWh [36].
524 In this work, a set of PGC costs possibilities varying between 0€/MWh to
525 500€/MWh with a step of 100€/MWh for both technologies wind and solar
526 is considered. The idea behind this set of values is to study a range of
527 different PGC costs to demonstrate the possible impact of such costs in the
528 final investment plan. Additionally, it is possible to analyze the differences of
529 plans in terms of NPV if during the project lifetime the PGC cost changes.
530 Figure 5 presents the single-line diagram of the 180 buses 30kV distribution
531 network which has one substation, 90 load points, 62.93km of overhead lines
532 (ACSR - aluminum conductor steel reinforced $3 \times 160mm^2$) and 150m of
533 underground cables (LXHIO1AV $3 \times 185mm^2$).

534 In this case study, the network planner intended to achieve a reduction
535 of at least 5% in SAIDI and SAIFI. The way to achieve these reductions is

investing in new lines construction. The places for new lines locations are depicted with the green dash lines. The stochastic model can also propose the substitution of the existent lines. Thus, for the connections between substation and network (bus 1 to bus 2; bus 1 to bus 102; bus 1 to bus 125), two cables types LXHIO1AV $3 \times 185mm^2$ or LXHIO1AV $3 \times 240mm^2$ can be chosen. All the other connections could be made by two type of aluminum overhead lines ACSR $3 \times 160mm^2$ or ACSR $3 \times 180mm^2$. In this case study, it is considered a high penetration of DG according to what is expected by the distribution system operator (DSO) [37]. A total of 99 DG (i.e., 55 wind farms and 44 PVs parks) are taken into account as can be seen in figure 5. DG penetration corresponds to 65% of the total installed power (wind generation represents 62% while PVs represents 3%). Each wind farm has four E40 500kW ENERCON wind turbines and follows the power curve represented in figure 6 [38]. This curve follows the relation (42).

$$\begin{cases} x < 2.50 \rightarrow y = 0 \\ 2.50 \leq x \leq 14.00 \rightarrow y = -0.0088x^4 + 0.3387x^3 - 2.8319x^2 + 15.827x - 16.051 \\ 14.00 < x \leq 25.00 \rightarrow y = 500.00 \\ x > 25.00 \rightarrow y = 0 \end{cases} \quad (42)$$

For simplicity the wind turbines in each wind farm are aggregated (2000kW of total installed power in each bus with wind turbines). PVs parks dispersed along the network have the characteristics presented in table 1 [39].

Table 1: Characteristics of the PV Module

Nominal Power (W)	85.00
Short Circuit Current (A)	1.62
Nominal Operating Temperature of the Cell ($^{\circ}C$)	45.00
Open Circuit Voltage (V)	56.70
Current at the Maximum Power Point (A)	1.41
Voltage at the Maximum Power Point (V)	45.50
Number of Modules	104
Number of Panels	15
Total Number of Modules	1560
Voltage High Temperature Coefficient ($>25^{\circ}C$) ($V/^{\circ}C$)	-0.1531
Voltage Low Temperature Coefficient ($-40^{\circ}C$ to $25^{\circ}C$) ($V/^{\circ}C$)	-0.1134
Current Temperature Coefficient ($A/^{\circ}C$)	6.4800×10^{-4}

The proposed methodology (section 2.2) can also determine the optimal size and location of the ESS in the network. Two types of ESS are considered

in this case study, as can be seen in table 2. Also, it is assumed that ESSs are purchased, installed and managed by the system operator and all buses, with exception of the substation bus (bus 1), are able to have an ESS. The maintenance costs already include the ESS replacement costs at 15 years lifetime.

Figure 5: Options of new lines investment in the actual 180-bus distribution network. Two types of overhead lines can be chosen, ACSR $3 \times 160mm^2$ or ACSR $3 \times 180mm^2$. The connections between substation and the network can be made by underground cables of two types LXHIO1AV $3 \times 185mm^2$ or LXHIO1AV $3 \times 240mm^2$.

Table 2: ESS types characteristics

ESS Type	Capacity (MWh)	Power Rate (MW)	Cost (€/kWh)	Cost (€)	Maintenance Cost (€/year)
ESS1	1.00	3.25	200.00	200 000.00	7 000.00
ESS2	3.00	5.75		600 000.00	20 000.00

Furthermore, five EV parking lots are connected to the buses 3, 69, 96, 107 and 161. Each of them has 20 car places with 22 kW of charge rate each, leading to a 2.2 MW of total charge power in the network. A simultaneity factor of one is considered in this case study. The considered cost for energy not supplied is 3€/kWh while for the power losses is considered 0.12€/kWh.

Figure 6: Wind power curve for the 500kW wind generators [38].

The seasons data are obtained following the method presented in subsection 2.1. A database between 2010-01-11 and 2017-09-04 for wind speed, radiation and temperature for the region where the network is located was used to determine the projections of wind and PV energy for the 16 scenarios. For energy demand the typical profile consumption curve of Portugal was used taking into account the 12% increase projection of the *EU Reference Scenario 2016: Energy, Transport and GHG emissions trends to 2050* [23] for Portugal. According with *Statistic Portugal* [24] the number of consumers for the considered region will be 6800 in 2050.

574 The overhead lines and cables costs can be found in table 3. It is impor-
575 tant to note that these costs are only for one line phase, so the multiplication
576 by 3 is needed (3 phases system).
577 It is considered that a new 30MVA MV transformer is needed for each new
578 installed feeder. It is assumed that the transformer purchase cost is 330,000€
579 and maintenance cost is 330€/year. Moreover, the maintenance cost of the
580 existent transformer is assumed to be 600€/year.

Table 3: Lines and Cables Costs

Line/Cable	Purchase Cost (€/km)	Maintenance Cost (€/km)
ACSR 160mm ²	32 000	1 600
ACSR 180mm ²	38 000	1 900
LXHIO1AV 185mm ²	45 000	900
LXHIO1AV 240mm ²	48 000	960

581 Each scenario used in this case study has its own probability, which is
582 determined by the method presented in subsection 2.1. The data used to
583 determine the probability of the considered scenarios is presented in table 4
584 and represent the Portuguese case. This table presents the number of days in
585 each season, time periods for each considered daily period (night, morning,
586 peak, afternoon) and their number of hours, and the total hours for each
587 daily period in each season. The probability tree diagram is presented in
588 figure 7.

Table 4: Seasons Periods

Seasons	Season Days	Hours Period				Hours/Day (h)				Hours/Season (h)			
		NT	MO	PK	AF	NT	MO	PK	AF	NT	MO	PK	AF
Spring	92	20-7	8-12	13-15	16-19	12	5	3	4	1104	460	276	368
Summer	92	20-6	7-13	16-16	17-19	11	7	3	3	1012	644	276	276
Fall	91	19-8	9-13	14-15	16-18	14	5	2	3	1274	455	182	273
Winter	90	18-8	9-12	13-14	15-17	15	4	2	3	1350	360	180	270

NT - Night / MO - Morning / PK - Peak / AF - Afternoon

Figure 7: Tree diagram for scenarios probabilities. NT - Night / MO - Morning / PK - Peak / AF - Afternoon

4. Results discussion

The proposed stochastic methodology is applied to the case study presented in section 3 to show its applicability. The optimization model is dealing with 1,197,051 constraints and 2,217,162 variables, where 65,158 are integer.

This proposed research work was developed in a computer with one Intel Xeon E5-2620 v2 processor and 16 GB of RAM running Windows 10 Pro using the MATLAB R2016a and TOMLAB 8.1 64 bits with CPLEX solver (version 12.5).

The execution time of the proposed methodology is compatible with planning timeframe, presenting an average value of 854 seconds (taking into account the execution of the method for the five PGC costs). The analysis of computer system resource impact is also evaluated by a memory test. MATLAB memory profiler was the used tool. This tool shows the peak memory for each function in the code. The higher observed value is 453MB, which is perfectly compatible with a wide range of available computers in the market.

4.1. Stochastic method applied to the actual network without investment alternatives

The output cost results, considering that the proposed stochastic method is applied to the actual network without any investment alternatives, i.e., without new lines possibility and ESS for the five PGC plan costs are presented in table 5.

Table 5: Actual Network Costs

Cost (€)	$PCost_{PGC}$ (€/MWh)				
	100	200	300	400	500
PGC	5 969 000.00	11 938 000.00	17 272 000.00	23 030 000.00	28 787 000.00
Losses	2 820 000.00	2 820 000.00	3 098 000.00	3 098 000.00	3 098 000.00
EENS	4 890 200.00	4 890 200.00	5 152 700.00	5 152 700.00	5 152 700.00
Lines Maintenance	9 182 900.00	9 182 900.00	9 182 900.00	9 182 900.00	9 182 900.00
Load Curtailment	0.00	0.00	0.00	0.00	0.00
Total Cost	22 862 100.00	28 831 100.00	34 705 600.00	40 463 600.00	46 220 600.00

As can be seen, the $PCost_{PGC}$ will have a strong influence in the total operation costs over the 30 years lifetime project. Losses and EENS cost increase when the $PCost_{PGC}$ is higher or equal to 300 €/MWh. The main reasons are the following:

- High $PCost_{PGC}$ leads to reduction in PGC power (since optimization avoids excess generation due to its higher cost). Hence, more power flows in the network increasing power losses and EENS, which are directly related to the power flow (see equation (12)).
- The chosen topology influences the power losses and EENS. When the $PCost_{PGC}$ is higher or equal to 300 €/MWh the line between bus 44 and bus 46 is open and the line between bus 46 and bus 51 is closed. For $PCost_{PGC}$ values lower than 300 €/MWh the line between bus 44 and bus 46 is closed and the line between bus 46 and bus 51 is open.

4.2. Stochastic method applied to the actual network with lines and ESS investment options

The output results for the proposed network with new lines and ESS investment options are shown in table 6. Table 7 shows the selected ESS quantities, size and location for each $PCost_{PGC}$ considered by the proposed model.

Table 6 shows that investments in ESS are needed only for $PCost_{PGC}$ above 300€/MWh. It is important to note that the maintenance cost includes the replacement of the ESS at 15 years lifetime. Regarding losses and EENS, it can be seen that their costs increase only for $PCost_{PGC}$ up to 300€/MWh, whereas a small reduction is identified for 400€/MWh and 500€/MWh $PCost_{PGC}$. A higher ESS capacity installed in the network

Table 6: Proposed Network Costs

Cost (€)	$PCost_{PGC}$ (€/MWh)				
	100	200	300	400	500
Lines/Feeders	1 387 200.00	1 464 000.00	1 459 200.00	1 459 200.00	1 459 200.00
ESS	0.00	0.00	200 000.00	600 000.00	1 000 000.00
Total Investment	1 387 200.00	1 464 000.00	1 659 200.00	2 059 200.00	2 459 200.00
PGC	2 641 800.00	4 906 700.00	5 606 200.00	6 526 100.00	7 368 500.00
Losses	2 369 300.00	2 399 400.00	2 565 600.00	2 564 900.00	2 564 900.00
EENS	4 494 900.00	4 548 800.00	4 802 800.00	4 797 300.00	4 797 100.00
Lines Maintenance	9 664 796.28	9 779 108.22	9 771 960.00	9 771 960.00	9 771 960.00
Load Curtailment	0.00	0.00	0.00	0.00	0.00
ESS Maintenance	0.00	0.00	208 381.00	625 143.00	1 012 100.00
Total Expenditures	19 170 796.28	21 634 008.22	22 954 941.00	24 285 403.00	25 514 560.00
Total	20 557 996.28	23 098 008.22	24 614 141.00	26 344 603.00	27 973 760.00

seems to mitigate the increase of EENS and power losses even with the rise in $PCost_{PGC}$.

Table 7: Selected ESS

ESS Type	Capacity (MWh)	Power Rate (MW)	$PCost_{PGC}$ (€/MWh)									
			100		200		300		400		500	
			Qt	Bus	Qt	Bus	Qt	Bus	Qt	Bus	Qt	Bus
ESS1	1.00	3.25	0	-	0	-	1	126	3	20	2	9
ESS2	3.00	5.75	0	-	0	-	0	-	0	-	1	126

Analyzing tables 5 and 6 and comparing the total cost difference between the actual network and the proposed network cost in the project lifetime, it is possible to see an increase of the difference when the $PCost_{PGC}$ also increases, varying between 10.08% and 39.48% for 100€/MWh and 500€/MWh respectively. In fact, when $PCost_{PGC}$ increases, the final cost with power generation curtailment ($P_{PGC} \times PCost_{PGC}$) takes a large part of the total cost in the actual network, as can be seen in the table 5. On the other hand, in the proposed network, the power generation curtailment cost is mitigated even when $PCost_{PGC}$ is high (table 6).

An economic analysis made in this work is presented in table 8. Each of the five investment plans exhibits an investment return during the lifetime project, so all of them are economically feasible. As mentioned in the case study section, the optimization goals also include the improvement of at least

5% in the SAIFI and SAIDI indexes. Comparing the indexes values obtained with the actual network and with the proposed network, it is possible to see in table 9 that the improvements are higher than 5% for all the considered investment plans.

Table 8: Economic Evaluation

Economic Indexes	$PCost_{PGC}$ (€/MW)				
	100	200	300	400	500
Payback (years)	11.19	6.06	4.20	3.79	3.54
IRR (%)	8.07	16.34	23.75	26.37	28.27
NPV (€)	2 302 956.57	5 730 235.10	10 086 429.56	14 111 959.99	18 237 745.40

655

Table 9: Reliability indexes comparison

Simulation	Index	$PCost_{PGC}$ (€/MWh)				
		100	200	300	400	500
Actual Network	SAIDI (h/customer)	23.62	23.62	24.48	24.48	24.48
	SAIFI (int/customer)	5.75	5.75	5.98	5.98	5.98
	EENS (MWh/year)	54.76	54.76	57.70	57.70	57.70
Planned Network	SAIDI (h/customer)	21.44	21.68	23.21	23.21	23.21
	SAIFI (int/customer)	3.81	3.86	4.13	4.13	4.13
	EENS (MWh/year)	50.33	50.93	53.78	53.71	53.71
Improvement (%)	SAIDI	9.24	8.22	5.19	5.19	5.19
	SAIFI	33.74	32.88	30.95	30.95	30.95
	EENS	8.08	6.98	6.79	6.90	6.90

Figure 8 presents an evaluation of the NPV considering that the PGC plan cost varies between 100 and 500 €/MWh after the investment implementation. In other words, it is analyzed the NPV of the project if the PGC plan cost changes after the investment decision is made. As can be seen in this figure, the investment result solution considering the resulting plan 1 (i.e., when $PCost_{PGC} = 100$ €/MWh) is just advantageous in terms of NPV for $PCost_{PGC}$ between a value close to 50 €/MWh and a value close to 150 €/MWh. As is shown in the figure, resulting plan 2 (i.e., when $PCost_{PGC} = 200$ €/MWh) does not present advantages when compared with

665 others. The resulting plan 3 (i.e., when $PCost_{PGC} = 300$ €/MWh) is the plan
 666 that presents better NPV for a high range of PGC costs, i.e., between a value
 667 close to 150 €/MWh and around 350 €/MWh. Resulting plan 4 (i.e., when
 668 $PCost_{PGC} = 400$ €/MWh) and resulting plan 5 (i.e., when $PCost_{PGC} = 500$
 669 €/MWh) present the better NPV for $PCost_{PGC}$ between 350 €/MWh and
 670 near to 500 €/MWh and higher or equal to 500 €/MWh, respectively. This
 671 analysis suggests that plan 3 is the one that presents lowest investment risks,
 672 unless the operator is certain that the $PCost_{PGC}$ is lower than 150 €/MWh
 673 or higher than 350 €/MWh.

Figure 8: NPV comparison considering different $PCost_{PGC}$. Five plans are evaluated with different $PCost_{PGC}$ between 100 and 500 €/MWh. NPV is calculated for each investment plan assuming that the $PCost_{PGC}$ might change after the investment implementation.

674 4.3. Stochastic and deterministic approaches comparison

675 The proposed solution was compared with a traditional method (deter-
 676 ministic). Since plan 3 presented the best NPV value for a high range of
 677 $PCost_{PGC}$, this plan was chosen to be compared with the deterministic
 678 model. Tables 10 and 11 present the economic and costs comparison for
 679 stochastic and deterministic approaches respectively. In table 10, it is pos-
 680 sible to see a considerable improvement in the three economic indexes when
 681 the stochastic approach is used. An improvement over the deterministic

approach of 59.90%, 170.62%, and 43.85% is verified for payback periods, IRR, and NPV, respectively. Table 11 shows a strong reduction in the investment, namely 1.0M € and 1.2M€ less for lines and ESS investment, respectively. For the total investment in the network, the proposed method presents a 56.47% reduction. Regarding expenditures, 33.22% total reduction is achieved when stochastic is used. However, as can be seen in table 11 two of the expenditures (power losses and EENS) present an increase with the proposed stochastic method (gray rows). This fact is related to the higher value of PGC power in the deterministic approach, which contributes to less power flow in the network. A general comparison between stochastic and deterministic approaches shows a total cost reduction of 35.54% when the proposed stochastic method is used. For better understanding, figure 9 shows graphically the improvement of the proposed method solution over a traditional approach.

Table 10: Economic comparison for stochastic and deterministic approaches

Economic Indexes	Stochastic	Deterministic	Difference	Economic Index Improvement (%)
Payback (years)	4.20	10.48	6.28	59.90
IRR (%)	23.75	8.78	14.97	170.62
NPV (€)	10 086 429.56	7 011 578.58	3 074 850.98	43.85

Table 11: Cost comparison for stochastic and deterministic approaches

Output		Stochastic (€)	Deterministic (€)	Reduction (€)	Reduction (%)
Investment	Lines/Feeders	1 459 200.00	2 611 950.00	1 152 750.00	44.13
	ESS	200 000.00	1 200 000.00	1 000 000.00	83.33
	Total	1 659 200.00	3 811 950.00	2 152 750.00	56.47
Expenditures	PGC	5 606 200.00	17 860 000.00	12 253 800.00	68.61
	Losses	2 565 600.00	1 539 900.00	-1 025 700.00	39.98
	EENS	4 802 800.00	3 816 600.00	-986 200.00	20.53
	Lines Maintenance	9 771 960.00	9 936 778.33	164 818.33	1.66
	Load Curtailment	0.00	0.00	0.00	0.00
	ESS Maintenance	208 381.00	1 220 500.00	1 012 119.00	82.93
	Total	22 954 941.00	34 373 778.33	11 418 837.33	33.22
Total		24 614 141.00	38 185 728.33	13 571 587.33	35.54

695

Figure 9: Investment and expenditures costs comparison for stochastic and deterministic approaches..

4.4. Network design after investment

The proposed expansion given by this work took into account the radial operation condition of the distribution networks. Thus, it is possible to see in figure 10 the optimal network design after investment. The new lines to be installed are presented in table 12. As can be seen in this table, a total of ten overhead lines of ACSR 160 type and one cable LXHIO1AV 185 between bus 1 and bus 102 are chosen by the proposed methodology. As a consequence of the selection of a cable between bus 1 and bus 102, a new transformer (30 MVA) is installed. ACSR 180 line type and LXHIO1AV 240 cable type were not chosen by the stochastic model.

Figure 10: Optimal network design after the investment in its expansion. Blue lines corresponds to the ones connected to feeder A while green lines corresponds to the ones connected to feeder B. The dash gray lines are unused lines, but exist in the network (lines from the actual network) and can be used in the operation/reconfiguration.

Table 12: Selected Lines / Cables by the Optimization Methodology

New Lines / Cables Type			
ACSR 160		LXHIO1AV 185	
Bus Out	Bus In	Bus Out	Bus In
93	60	1	102
72	67		
88	84		
101	97		
105	132		
143	146		
116	149		
141	151		
158	164		
173	165		

5. Conclusions

This research paper presented a new stochastic methodology considering seasonal impact to deal with the expansion planning problem of large distribution networks in a smart grid context with high DG penetration. The main features can be summarized as follows: a) seasonal and daily periods impact effect in the long-term distribution network planning in an SG context; b) optimal ESS size and location as well as the optimal type and location of new lines or the replacement of the existent ones; c) reliability improvement and the optimal radial topology.

The proposed stochastic methodology was tested using a case study of a real distribution network located in Portugal and compared with a traditional method (deterministic) to demonstrate the advantage of the former. It was verified that the proposed stochastic method presents a reduction around 13.6 M€ of the total cost (35.54% reduction) compared with the deterministic approach. Also, the considered economic indexes, i.e., payback, IRR, and NPV, improved by 59.90%, 170.62%, and 43.85% respectively. It was verified that the PGC cost, which accounts for the generation power excess penalty of RES, has a significant influence on the total cost. The investment in new lines and ESS are important to mitigate this cost. However, new strategies to deal with PGC cost must be sought to avoid excessive cost in the final customer's bill and also unnecessary investments in the network. The results suggest that the stochastic approach can be used as an efficient approach to deal with the inherent variability of the RES during the seasons of the year and the differences registered in daily periods.

730 The main drawbacks of the current methodology are: a) the proposed
731 method has not included yet the multi-period phased investment; b) the
732 uncertainty related to the projections (scenarios) is not considered.

733 As future work, the authors will improve the proposed method to include
734 the phased investment as well as incorporate the uncertainty in the scenarios
735 data. These two ideas can lead to high computational burden, so meta-
736 heuristics techniques may be considered to solve the problem. Moreover, it
737 will be interesting to include other forms of remuneration for DG and ESS
738 owners, whose role should be effectively separated from the operator duties.

739

740

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750

751 **Nomenclature**

752 **Indices**

753	bs	Substation
754	c	Line options
755	e	Energy storage systems
756	g	Distributed generator unit
757	i	Electrical buses
758	j	Electrical buses
759	lo	Loads
760	s	Scenarios

761	u	Energy storage system options
762	v	Electric vehicles parking lot
763	Parameters	
764	$\lambda_{(i,j,c)}$	Failure rate between bus i and bus j according to the chosen
765		line option c [failures/year]
766	$\lambda p_{(i)}$	Summation of all lines failure rate (at the view point of load
767		bus i) who represents the path between the load bus and the
768		substation/external supplier bus [failures/year]
769	ω_s	Scenario s probability
770	cef	Charge efficiency of energy storage systems
771	$CostPGC$	Power generation curtailment cost [€]
772	$CutCost$	Load curtailment cost [€/MWh]
773	def	Discharge efficiency of energy storage systems
774	$EENS$	Expected Energy Not Supplied [MW]
775	$EENSCost$	Expected Energy Not Supplied cost [€]
776	$ENSCost$	Energy not supplied cost defined by the regulator entity [€/MWh]
777	$FOR_{(i,j,c)}$	Forced outage rate between bus i and bus j according to the
778		chosen line option c
779	$I_{(i,j,c)}$	Nominal current between bus i and bus j according to the
780		chosen line option c [A]
781	$J_{eco(i,j,c)}$	Current density between bus i and bus j according to the
782		chosen line option c [A/mm ²]
783	$k_{(i,j,c)}$	Constant that depends on the type of service (one or three
784		phases) between bus i and bus j according to the chosen line
785		option c
786	$L_{(i,j,c)}$	Line length between bus i and bus j according to the chosen
787		line option c [km]

788	$LineCost$	Initial investment in new lines [€]
789	$LineMCost$	Lines maintenance cost [€]
790	$LossC$	Power losses cost defined by the regulator entity [€/MWh]
791	$LossCost$	Power Losses cost [€]
792	$LF_{(i,j,c)}$	Loss factor between bus i and bus j according to the chosen
793		line option c
794	$N_{(i)}$	Number of consumers in bus i
795	$PCost_{PGC}$	Power generation curtailment cost [€/MWh]
796	$r_{(i,j,c)}$	Repair time between bus i and bus j according to the chosen
797		line option c [hours]
798	$S_{ec(i,j,c)}$	Line section between bus i and bus j according to the chosen
799		line option c [mm ²]
800	$StCost$	Energy storage system cost [€/MWh]
801	$StMCost$	Energy storage system maintenance cost [€/year]
802	$U_{(i,j,c)}$	Unavailability between bus i and bus j according to the cho-
803		sen line option c [hours/year]
804	$Up_{(i)}$	Summation of all lines unavailability (at the view point of
805		load bus i) who represents the path between the load bus
806		and the substation/external supplier bus [hours/year]
807	$V_{(i)}$	Voltage in bus i (in DC model the voltage value is considered
808		1 <i>p.u.</i> for all buses)
809	vco	Cut-off speed [m/s]
810	$Dt_{(s)}$	Period duration of scenario s
811	$Flow^{max}_{(i,j,c)}$	Maximum admissible line flow between bus i and bus j ac-
812		cording to the chosen line option c [MW]
813	nDG	Number of DG units

814	$SAIDI^{max}$	Maximum Limit to System Average Interruption Duration
815		Index Limit [h/consumer.year]
816	$SAIFI^{max}$	Maximum Limit to System Average Interruption Frequency
817		Index [interruption /consumer.year]
818	$stCap_{(e,u)}$	Capacity of energy storage system e according to the chosen
819		energy storage system option u
820	A_{sr}	Irradiance [W/m^2]
821	I_M	Current at the maximum current [A]
822	I_{sc}	Short circuit current [A]
823	$P_{DGScenario(g,s)}$	Plank Constant
824	$pLoad(lo,s)$	Projected power demand for load lo in the scenario s [MW]
825	P_{rated}	Power rated [kW]
826	$P_{SMaxLimit(bs)}$	Maximum active power of substation bs [MW]
827	$P_{SMinLimit(bs)}$	Minimum active power of substation bs [MW]
828	T_I	Current temperature coefficient [$A/^{\circ}C$]
829	T_V	Voltage temperature coefficient [$V/^{\circ}C$]
830	T_{Amb}	Ambient temperature [$^{\circ}C$]
831	V_M	Voltage at the maximum power [V]
832	v_r	Rated speed [m/s]
833	V_w	Wind speed [m/s]
834	v_{ci}	Cut-in speed [m/s]
835	V_{OP}	Open circuit voltage [V]
836	$\rho_{(i,j,c)}$	Line resistivity at operating temperature between bus i and
837		bus j according to the chosen line option c [$\Omega \cdot mm^2/km$]

838 **Sets**

839	Ω^b_E	Set of ESS bus
840	Ω^b_j	Set of buses without substation buses
841	Ω^b_L	Set of load buses
842	Ω^b_V	Set of EV buses
843	Ω^b_{BS}	Set of substation buses
844	Ω^{nd}_{DG}	Set of non-dispatchable DG
845	Ω_B	Set of buses
846	Ω_E	Set of ESS
847	Ω_l	Set of lines
848	Ω_O	Set of line options
849	Ω_s	Set of scenarios

850 **Variables**

851	I_{PV}	Cell current [A]
852	V_{PV}	Cell voltage [V]
853	$\Delta p_{(i,j,c,s)}$	Linearized power losses between bus i and bus j according
854		to the chosen line option c [MW]
855	$EVP_{(v,s)}$	Power charge for v EV parking lot in scenario s [MW]
856	$Flow_{(i,j,c,s)}$	Power flow between bus i and bus j according to the chosen
857		line option c in scenario s [MW]
858	$SAIDI$	System Average Interruption Duration Index [h/consumer.year]
859	$SAIFI$	System Average Interruption Frequency Index [interruption/consumer.year]
860	$a_{(e,u)}$	Binary decision variable $\{0,1\}$ for energy storage system e of
861		the option u

862	$D_{(g)}$	Fictitious load for each distributed generator g
863	$d_{(i,j,c)}$	Fictitious flow associated with branch i,j for c line option
864	F_F	Fill factor
865	P_w	Wind power output [kW]
866	P_{cell}	Solar power output [W]
867	$p_{Charge(v,s)}$	ctive power charging of EV Parking Lot v for scenario s [MW]
868	$p_{DG(g,s)}$	Power of distributed generation g in scenario s [MW]
869	$p_{LoadCut(lo,s)}$	Power load curtailment in load lo for scenario s [MW]
870	$p_{PGC(g,s)}$	Power generation curtailment of distributed generator g in
871		scenario s [MW]
872	$p_{storage(e,u,s)}$	Power charge/discharge of energy storage systems e accord-
873		ing to the chosen energy storage system option u for scenario
874		s [MW]
875	$p_{Supplier(bs)}$	Generation power of the substation bs [MW]
876	T_{cell}	Cell temperature [$^{\circ}C$]
877	$y_{(i,j,c)}$	Binary decision variable $\{0,1\}$ for the line usage between bus
878		i and bus j according to the chosen line option c

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