Energy Proceedings
Vol 44, 2024
ISSN 2004-2965

Optimizing Smart Distribution Network Expansion Incorporating the Seasonal Impacts, CO_2 Emissions and Resources Remuneration: A Multi-Stage Stochastic Framework

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ABSTRACT: Making the leap toward a clean future can be challenging. Network planning is essential to combat those challenges. This research work focuses on the planning field, dealing with daily uncertainty, energy storage systems, remuneration of distributed resources, and CO_2 emissions while considering the impacts of the seasons on the network expansion. In that regard, a multi-stage stochastic optimization model is proposed to minimize all planning costs and CO_2 emissions. The model is tested in a 180-bus realistic 30kV medium-voltage distribution network in the Leiria district, Portugal, with high renewable energy penetration, in a 30-year lifetime project.

Keywords: Carbon Emissions, Energy Storage Systems, Remuneration of Resources, Renewable Energy Sources, Seasonal Impacts, Uncertainty

1. INTRODUCTION

The landscape of modern networks requires a collective effort from policymakers and network contributors alike to meet the desired target of 40% renewable energy source (RES) penetration by 2030, imposed by the European Union. Thus, it is mandatory to adequately prepare the network in the planning stage without disregarding the involving factors, such as energy storage systems (ESS), uncertainty, remuneration of distributed generation (DG) [1], CO_2 emissions [2], while also attributing importance to the seasonal effects [3]. Kayal et al. present a planning approach for integrating solar, wind, and capacitor banks in an electric power distribution network [4]. The model seeks to lower costs, losses, emissions, voltage stability, and network security. The model uses a multi-objective particle swarm optimization algorithm with fuzzy decision-making to find RES and capacitor units' optimal location and size on a 28-bus Indian rural distribution network. The results show that the proposed model outperforms single renewable energy sources or capacitor units. Home-Ortiz et al. [5], propose a stochastic mixed-integer convex programming model for long-term distribution system expansion planning accounts for greenhouse gas emissions and predicts the best substation reinforcement, conductor replacement for overloaded feeders, and renewable and dispatchable distributed generation unit location and sizing. The model accounts for wind production power and electricity usage unpredictability. The model is tested under different scenarios on a 34-node distribution system and a 135-node real network. The model generates an economic investment plan that reduces distribution network carbon emissions. Lima et al. in [6], provide a mathematical model for electrical distribution system expansion planning that balances cost and CO2 reduction. Investments for renewable and non-renewable substations, circuits, and distributed generation units are considered. Demand and renewable generation uncertainties are addressed using two-stage stochastic programming based on scenarios. The enhanced-constrained method generates Pareto optimum solutions for multi-objective problems. A 54-node distribution system case study shows the trade-off between the two objectives and how renewable distributed generation affects expansion.

Melgar Dominguez et al. in [7] use a mathematical model to optimize electrical distribution system (EDS) architecture by considering RES location and quantity, capacitor banks, and ESS. The idea reduces EDSs' energy, investment, and environmental impacts while improving their technical performance. The model adjusts for photovoltaic generating and consumption uncertainties using external uncertainty indexes. The mixed-integer nonlinear programming model is linearized and solved using commercial tools. The model saves money, improves voltage, and reduces emissions on a 135-node distribution system.

Lastly, Lima et al. in [8] describe a mathematical model for allocating electric vehicle charging stations (EVCSs) and RES in EDS. The model considers the uncertainties of traditional consumption, EV demand, renewable generation, and the environmental impact of

This is a paper for 15th International Conference on Applied Energy (ICAE2023), Dec. 3-7, 2023, Doha, Qatar.

CO2 emissions. A commercial solver solves the model, written as a two-stage stochastic mixed-integer linear programming problem. The results suggest that allocating EVCSs and RES simultaneously can minimize the EDS's total cost and CO2 emissions. The paper also conducts sensitivity analysis with various CO2 emission rates and levels of EV adoption.

The proposed advancement in the state-of-the-art corresponds to an innovative stochastic methodology to adequately implement all the mentioned topics (Uncertainty, ESS, Remuneration of resources, seasonal impacts, and CO_2 emissions). While most of them are commonly addressed, they are never considered together, so we aim to give each of them equal importance, as a contribution to the field. To the best of the authors' knowledge, the answer to "Can a stochastic optimization model for long-term distribution network planning considering uncertainty, ESS, remuneration of DG, and CO2 emissions be economically viable?" has not been answered. The proposed model is applied to a 180-bus network with one substation, 42 Wind farms, 33 PV parks, three biomass generators, two ESSs, 90 loads, and five electric vehicle parking lots (EVP). This paper is organized into the following sections: 1- Introduction where the topic and relevant literature are briefly addressed, 2-Proposed Methodology where the proposed method is explained; 3-Case Study and 4-Results are the details and results of the study, and lastly, 5-Conclusions, where the conclusions are drawn.

2. PROPOSED METHODOLOGY

The proposed method is explained in this section.

2.1 Scenario definition and uncertainty application

The main scenarios of this model follow [9], where the division of the seasons and daily periods remains the same. From these 16 main scenarios, four variations are generated for each, resulting in 64 total sub-scenarios.

Table 1. Multiplicative Factors for PV/Wind/Load

Season	Multiplicative Factor for PV/Wind/Load			
	Morning	Peak	Afternoon	Night
Summer	1.40/1.00 /0.99	3.20/1.60 /1.11	2.40/1.00 /0.91	0.05/0.80 /0.59
Spring	1.00/1.00 /1.00	2.60/1.40 /1.12	1.40/1.00 /0.92	0.05/0.80 /0.65
Fall	1.00/1.00 /1.03	2.20/1.40 /1.16	1.40/1.00 /0.93	0.05/0.80 /0.65
Winter	0.60/1.00 /1.03	1.40/1.40 /1.14	1.00/1.00 /0.95	0.05/0.80 /0.69

Multiplicative factors were applied to the sub-scenarios, which resulted from a study of wind, PV, and load behavior from Portugal from 2017-2022. Wind and PV data are obtained from [10] and load from [11]. The results are shown in Table 1. Spring morning was chosen to have 1.00 as factors, so all the other scenarios can be compared directly to it.

2.2 Remuneration of resources and CO2 considerations

The values in Table 2 were found by calculating the averages of the reported values in [12], [13]. A price for regular use was decided, as well as a price for generation curtailment, dubbed as "Excess Price". The ESSs in buses 31 and 87 present a contract between the DSO and a third party, allowing the DSO to free use of 25% of the ESS. Any new ESS that may be installed is assumed to be owned by the DSO.

Table 2. Remuneration Prices of Each Technology

Generation Source	Normal Use Price (m.u./MWh)	Excess price (m.u./MWh)
Owned by the DSO		
Substation	55	300
Biomass	45	300
ESS	40	300
Owned by another party, which needs compensation		
Wind Farms	45	150
PV Parks	45	150
ESS (Bus 31/87, in contract)	30	150
ESS (Bus 31/87, out of contract)	400	1000

As for the values in Table 3, they were found as an average of [14], [15]. The value corresponding to the emissions costs is 51 m.u./ton, the official social cost of carbon in the United States of America [16].

Table 3. Emission Rates of Each Technology

	PV	Wind	ESS	Biomass	Substation
Emission Rate (tons/MWh)	0.0584	0.0276	0.2012	0.7550	0.6079
Costs of Emission (m.u./ton)	51				

2.3 Optimization model

The suggested multi-stage stochastic model ensures a radial topology and permits investments in ESSs and possible additional power lines, feeders, and their corresponding transformers and ESSs. The project has a 30-year lifespan cycle. The suggested model is written as MILP. The model provides the following information regarding the decision variables:

- Power required by DSO (substation, biomass, and any ESS to be added apart from the ones in buses 31/87);
- Power generation curtailment of DG;
- Size and location of ESS;
- Optimal network topology;
- Optimal power flow for each line in each sub-scenario;

- The model outputs the following information:
- Every associated network-specific cost: new lines, lines' maintenance, expected energy not supplied (EENS), power losses, ESS installation and maintenance, load cut, and power generation curtailment;
- System average interruption duration index (SAIDI);
- System average interruption frequency index (SAIFI);
- Cost of the power required by DSO (substation, biomass, and any ESS to be added apart from the ones in buses 31/87) yearly;
- Remuneration to the networks' third-party generation providers (PV, Wind, ESS buses 31/87);
- Economic analysis as a comparison to the original network;
- CO2 emissions.

The characteristics of the EVPs and all the wind turbines and PV modules follow [9].

There are ESSs installed on buses 31 and 87, but the model allows the installation of as many as it sees fit.

The cost for power losses is considered 120 m.u./MWh.

The objective is to minimize all associated costs (1).

$$PC = PC_1 + PC_2 + PC_{CO2} \tag{1}$$

PC_1/PC_2 represents the stochastic model - 1st/2nd stage, and PC_{CO2} as the carbon emission costs. The objective function follows the one presented in [9], but now includes (2) to PC_2 (resources remuneration) and (3) to PC_{CO2} (emissions).

$$\mathrm{Re}\,mun = \begin{bmatrix} P_{Sub(bs)} \cdot Sub_{\text{Price}} + \sum_{bio \in Bio} P_{Bio(bio,s)} \cdot Bio_{\text{Price}} + \\ \sum_{pv \in PV} P_{PV(pv,s)} \cdot PV_{\text{Price}} + \sum_{wi \in WI} P_{WI(wi,s)} \cdot WI_{\text{Price}} \end{bmatrix} \tag{2}$$

$$PC_{CO_2} = \sum_{s \in \Omega_S} \left[\begin{pmatrix} P_{\text{Sub(bs)}} \cdot \iota_{bs} + \sum_{bio \in Bio} P_{\text{Bio(bio,s)}} \cdot \iota_{Bio} + \\ \sum_{pv \in PV} P_{\text{PV(pv,s)}} \cdot \iota_{PV} + \sum_{wi \in WI} P_{WI(wi,s)} \cdot \iota_{WI} + \\ + \sum_{e \in E} P_{\text{E(e,s)}} \cdot \iota_E \end{pmatrix} \cdot \varpi_s \cdot EC_{CO_2} \right] \tag{3}$$

Where P_{Sub} is the amount of generation provided by the substation, Sub_{Price} is the price for that respective generation, and ι_{bs} is the emission rate of the substation. The same pattern applies to the other technologies. ϖ_s represents the scenario probability and EC_{CO2}, the social cost of emissions, in m.u./ton.

The model is also subject to the following constraints:

- Power balance;
- Power flow limit;
- Unidirectionality of power flow;
- Insurance of radial topology;
- Avoidance of island creation;
- Substation, biomass, and ESS maximum capacity;
- ESS charge and discharge rate;
- Price adaptation of ESS;
- SAIDI and SAIFI limits;
- Generation and load curtailment limit.

3. CASE STUDY

The method in section 2. was used to analyze a 30kV MV distribution network in the Portuguese district of Leiria. The network comprises 180 buses, 90 loads, 5 EVPs, 2 ESSs, 42 wind farms, 33 PV parks, three biomass plants, and a 20 MW substation. As suggested, the network will permit the potential installation of new power lines.

$$Minimize PC = PC_1 + PC_2 + PC_{CO2} + FT_{risk}$$

There is an aim to reduce the SAIDI and SAIFI values by at least 10% from their original values of 24.48 (h /customer) and 5.98 (interruptions/customer), respectively. The initial network, where the model will apply the changes, is an adaptation of the network in [9].

4. RESULTS DISCUSSION

The final network configuration is depicted in Fig. 1.

The model proposes installing several new lines, e.g., 103-105, a new feeder installation, and a new transformer in 1-125. The final values of SAIDI and SAIFI are 20.39h/customer and 4.10 int/customer, corresponding to a 20.11% decrease for the SAIDI and 31.5% for the SAIFI. The total listing of costs is in Table 4.

Table 4. Total listing of costs

Investments	Lines (w/ Transformer Cost)	1 253 550 m.u.
	ESS	400 000 m.u.
Expenditures	Excessive Generation	5 654 m.u.
	Power Losses	220 688 m.u.
	Expected Energy Not Supplied	1 235 604 m.u.
	Lines Maintenance	8 433 230 m.u.
	ESS Maintenance	864 392 m.u.
Remuneration (Yearly)	Substation	3 900 161 m.u.
	Biomass	291 880 m.u.
	Wind	499 340 m.u.
	PV	144 910 m.u.
	Storages	16 252 m.u.
CO2 Emissions	Substation	2 169 908 m.u./42 547 tons
	Biomass	248 099 m.u./4 865 tons
	Wind	15 619 m.u./306 tons
	PV	9 591 m.u./188 tons
	Storages	201 m.u./4 tons
Total Costs		**19 691 032 m.u.**

The economic analysis regarding the model can be seen in Table 5. This analysis is a comparative evaluation of the original network, which incurred a total cost of 29 705 600 m.u. (adaptation of the network in [9]).

Table 5. Economic Analysis

Net Present Value (NPV)	8 356 240 m.u.
Payback	4.92 years
Internal Rate of Return (IRR)	20.26%

Despite the inclusion of resource remuneration and CO_2 emission costs, the proposed model demonstrates a compelling economic appeal, characterized by a relatively abbreviated payback period (4.92 years).

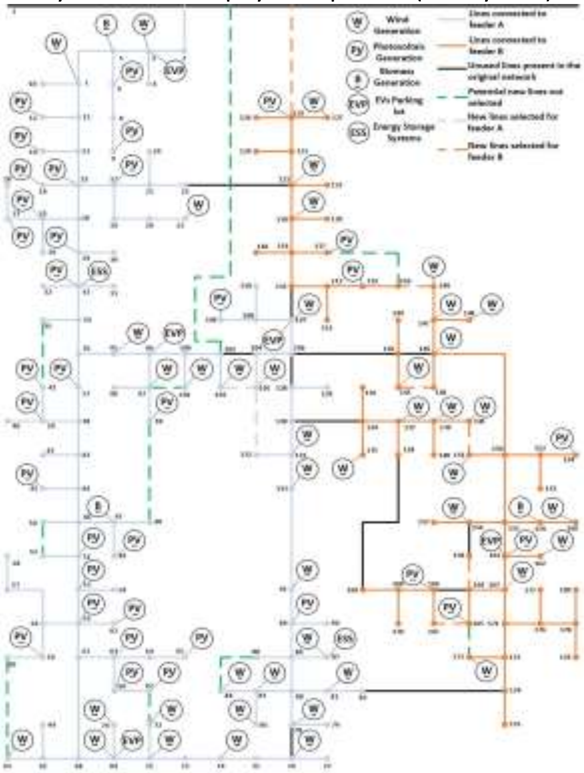

Fig. 1 Optimal Network Topology

5. CONCLUSIONS

The efforts to transition to a cleaner energy landscape are necessary, even if complicated. Considering aspects such as uncertainty, storage, remuneration of resources, and CO_2 emissions is a must, especially at the network planning stage. This work proposed an innovative stochastic optimization model that attributes adequate importance to all relevant aspects of modern networks. The economic analysis proves that the model is economically interesting, with an NPV of 8 356 240 m.u. and a relatively short Payback of 4.92 years. For future work, the authors plan to implement multi-period investment.

ACKNOWLEDGMENTS

This research has received funding from FEDER funds through the Operational Programme for Competitiveness and Internationalization (COMPETE 2020), National Funds through the FCT Portuguese Foundation for Science and Technology under project UIDB/000760/2020, CEECIND/00420/2022 and from the NGS Innovation Pact - New Generation Storage (C644936001-00000045),co-financed by NextGeneration EU, through the Incentive System Agendas for Business Innovation, within the scope of the Recovery and Resilience Plan (PRR). José Almeida is supported by FCT with Ph.D. Grant 2022.09590.BD. Fábio Castro, Bruno Canizes, João Soares, José Almeida, and Zita Vale are with GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development, LASI – Intelligent Systems Associate Laboratoy and Polytechnic of Porto, Portugal.

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