A Risk-Based Planning Approach for Sustainable Distribution Systems Considering EV Charging Stations and Carbon Taxes

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***Abstract*—Adopting distributed energy resources (DERs) is the key to a low-carbon future in electrical distribution systems (EDS). However, integrating DERs increases the uncertainties in the distribution system expansion planning (DSEP). Thus, the long-term DSEP faces a planning risk brought by the uncertainty of demand, electric vehicle (EV) demand, renewable production, and energy prices. Therefore, this work proposes a novel model for the multi-period planning of EDSs and DERs considering conditional value at risk (CVaR) to manage fluctuations in generation cost and carbon emissions. The proposed mathematical model aims to minimize the net present cost related to investment, operation, and risk. Unlike previous approaches, uncertain behavior of demand growth per planning period is addressed, and the risk is evaluated from two perspectives: planning costs and carbon taxes. Investments in substations, lines, renewable distributed generation, EV charging stations, and energy storage systems are considered. The uncertainties associated with the variability of renewable generation and demand are modeled through a set of scenarios. Finally, the model was evaluated using the 24 and 54-bus EDS. Thus, the proposal is a flexible tool that can be used for different purposes (e.g., carbon taxes, budget limits).**

***Index Terms*—Carbon emissions, conditional value at risk, distributed energy resources, distribution system expansion planning, energy storage systems, EV charging station, renewable generation.**

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NOMENCLATURE

Indices

a	Index of conductor types.
b/r	Index of candidate buses for allocation of ESS/ EVCSs.
c	Index of types of EV chargers.
d	Index of substation buses.
$i/\ ij$	Index of buses/lines.
k/u	Index of candidate buses for allocation of WT/PV units.
p/t	Index of planning periods.
s/s^{ϖ}	Index of scenarios/index of scenarios s in time block ϖ.

Parameters

$\beta^{em/pl}$	Parameters used to represent the trade-off between expected cost and risk aversion.
ζ_i^{s}	CO_2 emission rate of energy provided by the grid.
$\eta^{\mathrm{ES}-/+}$	Charging/discharging efficiency rate for ESS.
λ	Duration in years of each planning period.
π_s	Occurrence probability of scenario s.
$\varrho_{i,p}$	Apparent power demand at bus i and period p.
ϱ_d^i	Initial apparent power capacity of substation at bus i.
ϱ_d^f	Apparent power capacity for reinforcing substation at bus i.
τ	Interest rate.
$\bar{b}$	Maximum limit for the absolute value of variable $b_{ij,\omega,p}$.
C_s^{ctax}	Cost of carbon tax.
C_b^{ES}	Cost of ESS.
C_c^{EV}	Cost of EV charger type c.
$C_{ij,a,p}^{\mathrm{L}}$	Cost for the installation of line ij using conductor type a
C_u^{pv}	Cost of PV unit at bus u.
C_i^{s}	Cost of substation construction at bus i.
$C^{\mathrm{op,pv}}$	Operational & Maintenance cost for PV units.
$C^{\mathrm{op,wt}}$	Operational & Maintenance cost for WT units.
C_k^{wt}	Cost for WT unit investment at bus k.
$D_{s,p}^{\mathrm{EV}}$	EV aggregated demand, in scenario s and period p.
d_s	Duration (hours) of scenario s.
f_s^{D}	Demand factor of scenario s.
f_s^{pv}	PV generation factor of scenario s.
$\bar{I}_{ij}$	Maximum current of line ij.
l_{ij}	Length of line ij.
$\bar{N}_b^{\mathrm{ES}}$	Maximum number of ESS to be installed.

$\bar{N}_c^{\mathrm{EV}}$	Maximum number of EV chargers type c to be allocated.
$\bar{N}_u^{\mathrm{pv}}$	Limit of PV units to be allocated at bus u.
$P_{i,p}^{\mathrm{D}}/Q_{i,p}^{\mathrm{D}}$	Active/reactive power demand at bus $\boldsymbol{i}$ and period p.
$P_{\mathrm{c}}^{\mathrm{EV}}$	Capacity of EV charger type c
P_b^{ES}	Maximum active power capacity of ESS at bus b.
$\bar{P}_k^{\mathrm{wt}}$	Active power capacity of WT units at bus k.
$\bar{P}_u^{\mathrm{pv}}$	Active power capacity of PV units at bus u.
R_a	Conductor resistance.
$\bar{V}/\underline{V}$	Maximum and minimum voltage limits.
X_a/Z_a	Conductor reactance/impedance.

Continuous Variables

$\varrho_{i,s,p}^{\mathrm{sqr}}$	Square of the apparent power supplied by substation at bus i, scenario s, and period p.
$\psi_{ij,p}^{-/+}$	Variable associated with the backward/forward direction of line ij and period p.
$b_{ij,s,p}$	Variable used in the calculation of the voltage drop of line ij, at scenario s, and period p.
CVaR^{em}	Risk measure related to planning costs.
CVaR^{pl}	Risk measure related to carbon tax.
CVaR^{total}	Sum of the risk measure related to planning cost and carbon tax ($\mathrm{CVaR}^{pl} + \mathrm{CVaR}^{em}$).
$D_{r,s,p}^{\mathrm{EVCS}}$	Charging demand in EVCS at bus r, scenario s and period p.
$I_{ij,a,s,p}^{\mathrm{sqr}}$	Square of current through line ij for conductor a in scenario s and period p.
$\hat{I}_{ij,s,p}^{\mathrm{sqr}}$	Square of the current through line ij in scenario s and period p.
$P_{ij,a,\omega,p}$	Active power flow through line ij for conductor a in scenario s and period p.
$\hat{P}_{ij,s,p}$	Active power flow through line ij in scenario s and period p.
$P_{b,s,p}^{\mathrm{ES}-}$	Active power stored of ESS at bus b, scenario s, and period p.
$P_{b,s,p}^{\mathrm{ES}+}$	Active power provided by ESS at bus b, scenario s, and period p.
$P_{u,s,p}^{\mathrm{pv}}$	Active power provided by PV at bus u, scenario s, and period p.
$P_{d,s,p}^{\mathrm{s}}$	Active power provided by substation at bus d, scenario s, and period p.
$P_{k,s,p}^{\mathrm{wt}}$	Active power injected by WT at bus k, scenario s, and period p.
$Q_{ij,a,s,p}$	Reactive power flow through line ij for conductor a in scenario s and period p.
$\hat{Q}_{ij,s,p}$	Reactive power flow through line ij in scenario s and period p.
$Q_{u,s,p}^{\mathrm{pv}}$	Reactive power injected by PV at bus u, scenario s, and period p.
$Q_{d,s,p}^{\mathrm{s}}$	Reactive power by the substation i at bus d, scenario s, and period p
$Q_{k,s,p}^{\mathrm{wt}}$	Reactive power injected by WT at bus k, scenario s, and period p.
$V_{i,s,p}^{\mathrm{sqr}}$	Square of the voltage at bus i, scenario s, and period p.
$z_{ij,a,p}$	Operational variable associated with line ij, conductor a, at period p.

Integer and Binary Variables

$N_{b,p}^{\mathrm{ES}}$	Integer variable that indicates the number of ESS at bus b and period p.
$N_{r,c,p}^{\mathrm{EV}}$	Integer variable that indicates the number of EV chargers at bus r, type c and period p.
$N_{u,p}^{\mathrm{pv}}$	Integer variable that indicates the number of PV unit at bus u and period p.
$x_{r,p}^{\mathrm{EV}}$	Investment variable for installing an EVCS at bus r and period p.
$x_{ij,a,p}^{\mathrm{L}}$	Binary variable for investment in line *ij* using conductor type a, and period p.
$x_{d,p}^{\mathrm{S}}$	Binary variable for construction of substation at bus d and period p.
$x_{k,p}^{\mathrm{wt}}$	Binary variable for allocation a WT unit at bus k and period p.

I. Introduction

Carbon dioxide is the main greenhouse gas produced by human activities and has been driving changes in the global climate. Concern related to environmental problems and climate change has encouraged the development of distributed energy resources (DERs) to support the decarbonization of power systems [1]. DERs include distributed generation (DG), energy storage systems (ESSs), and controllable loads, e.g., electric vehicles (EVs). Recently, the use of EVs has been identified as a key action to collaborate with the goals of the Paris agreement. At the 26th UN Climate Change Conference of the Parties (COP26), governments, companies, and other organizations committed to a zero-emission transport future, accelerating the pace of electrification. The goal is for all new vehicle sales to be zero-emission by 2040 [2].

Adoption of green-based DERs is the key to a future with low carbon footprint in electrical distribution systems (EDS). However, the increase of such resources brings challenges in the planning of EDS related to technical, economic, and environmental factors [3]. Therefore, studies in the area of distribution system expansion planning (DSEP) have directed efforts to address the integration of DERs [4], [5], [6], [7], [8]. A robust optimization model has been used in [4] to resolve the problem with the allocation of renewable energy sources in a short-term planning period. In [5], the long-term DSEP has been solved through a hybrid approach based on classical optimization methods and metaheuristics. Such a proposal addresses the allocation of DG units and ESS as in [6]. A multi-objective model that aims to minimize carbon emissions and investment and operational costs is proposed in [7]. Moreover, a mixed-integer linear programming (MILP) model has been formulated in [8] to define the investment in lines and ESS, taking into account the presence of EV parking lots, photovoltaic (PV) generation, and wind generation in the distribution systems.

EVs are still poorly addressed in DSEP specialized literature [9], [10]. Existing works are mainly focused on operational aspects of EVs [11]. Most works that address the planning of

EV charging stations (EVCSs) do not consider the planning of distribution networks [12], [13]. Just recently some works in DSEP have proposed the simultaneous planning of EVCS and distribution networks [14], [15], [16], [17], [18]. For instance, the integrated planning of EVCSs and EDS is investigated in [14], including multi-period investments in non-renewable DG units and capacitor banks. That proposal simplifies uncertainties associated with the EV demand, representing the state of charge (SoC) as a deterministic parameter. In [15], EV uncertainties are better represented using a method based on travel patterns. However, the operation of distribution networks is modeled through a DC power flow, a formulation unsuitable for EDS [19]. A MILP model for solving the DSEP was formulated in [16], including constraints that limit carbon emissions. Environmental issues are also considered in [17], which presents a stochastic linear model to define multi-period investment actions in EDS. A linear model has also been formulated in [18] to handle the joint planning of EVCS and distribution networks. In that work, a probabilistic algorithm is used to incorporate the uncertainty of the problem.

The inclusion of EVs as well as renewable generation contributes to increasing the uncertainties of DSEP. Thus, the DSEP faces risks caused by uncertainty in the behavior of renewable generation, demand, and EVs. Hence, risk measurement plays a vital assignment in optimization problems under uncertainty, affording pertinent information to system planners. Some planning studies of EDS have adopted a risk measure using conditional value at risk (CVaR) [20], [21]. Risk-based planning was proposed in [20] to resolve the classic planning problem with investment only in lines; however, risk is evaluated under uncertainties related to energy demand and price. Therefore, the major sources of uncertainty in modern planning associated with renewable generation and EV demand are not addressed in [20]. In contrast, a stochastic bi-level model was formulated in [21] to solve the planning of microgrids considering investments in DG units, ESS, and distributed reactive sources. Nevertheless, both works [20], [21] did not consider the EVs in the planning problem.

The specialized literature lacks a risk-based planning approach to the modern DSEP problem that includes DERs and EVCSs. In addition, the uncertainties inherent to the planning problem (e.g., power output of renewable generation) directly impact greenhouse gas emissions. Thus, there are risks associated with environmental components that have been neglected. Another important aspect is that most works are limited to addressing the uncertainties related to the hourly variability of stochastic parameters. On the other hand, to the best of the author's knowledge, long-term uncertainties (e.g., demand growth, carbon tax per planning period) have not been addressed in the DSEP proposals. Such uncertainties can strongly impact expansion plans obtained for the DSEP problem.

Therefore, this work fills the gap in the specialized literature by proposing a novel model for the multi-period planning of EDS and EVCSs considering CVaR to control the risk of planning cost fluctuation and carbon emissions. Unlike previous approaches, the risk is evaluated from two perspectives: operational costs and carbon taxes. The expansion alternatives are the following: construction of substations and lines, allocation of renewable DG units/ESS, and installation of EVCSs. The uncertainties related to the variability of solar/wind production, conventional demand, EV demand, and energy price are modeled using a set of discrete scenarios. Moreover, different from other proposals, the uncertainty introduced by demand growth and carbon taxes is accounted for. These long-term uncertainties are represented in this work through a scenario-based model due to its flexibility in adding new uncertainties. It is important to highlight that presenting a new uncertainty modeling method is outside this work's scope, while the differential of this proposal is to address long-term uncertainties. Finally, the main contribution of this work is to present a new risk-based planning strategy considering different risk perspectives aiming at sustainable proposals.

Table I compares the proposed model here and the previous works proposed for the DSEP problem. Finally, the main contributions of this work are presented as follows:

i) A novel risk-based planning strategy for the multi-period planning of EDS and EVCSs. Investment in substations, lines, PV units, wind turbine (WT) units, EVCSs, and ESS are considered.
ii) Evaluation of risk from two perspectives: planning costs and carbon taxes. Conditional value at risk (CVaR) is used as a risk management to control the risk of planning cost fluctuation and carbon emissions.
iii) A two-stage stochastic MILP model to optimally resolve the distribution system expansion planning using efficient commercial solvers. The uncertainties associated with the variability of solar/wind generation, conventional demand, EV demand, and energy price are addressed and modeled by a set of discrete scenarios.
iv) Furthermore, this work addresses the long-term uncertainty related to demand growth and carbon taxes according to the planning period.

The next sections of this paper are structured as follows. Section II presents the proposed model for the risk-based planning of EDS and EVCSs. Section III describes the case study and the application of the proposed model. Finally, in Section IV, the conclusions are described.

II. Problem Formulation

The proposed planning strategy considers simultaneous investment in substations, lines, renewable DG units, EVCSs, and ESS, as well as short-term and long-term uncertainties. Short-term uncertainties are related to variability of solar irradiation, wind speed, conventional demand, EV demand, and energy prices. On the other hand, long-term uncertainties are associated with demand growth and carbon tax per planning period. The risk-based DSEP is formulated as a two-stage stochastic MILP model. Risk is assessed from two perspectives: generation cost fluctuation and carbon emissions. Risk related to environmental aspects is transformed into a monetary term using carbon taxes, a cost-based tool that establishes a tax per ton of carbon emissions [6].

Similar to [16], [17], a centralized strategy is used here to solve the joint planning of EDS and EVCS. Such an approach provides

TABLE I
TAXONOMY OF PROPOSALS FOR THE DSEP PROBLEM

Reference	Solution method	Multi-period approach	Investment options					Long-term uncertainty	Risk measure	Risk related to carbon tax
			S/L	WT units	PV units	EVCSs	ESS			
[3]	1	-	✓	✓	✓	-	-	-	-	-
[4]	1	✓	✓	✓	✓	-	-	-	-	-
[5]	3	✓	✓	✓	✓	-	✓	-	-	-
[6]	1	✓	✓	✓	✓	-	✓	-	-	-
[7]	1	✓	✓	✓	✓	-	-	-	-	-
[8]	1	-	✓	-	-	-	✓	-	-	-
[9]	1	✓	-	✓	✓	✓	-	-	-	-
[11]	1	-	-	-	-	✓	-	-	-	-
[12]	2	✓	✓	-	-	✓	-	-	-	-
[13]	1	✓	-	-	-	✓	-	-	-	-
[14]	1	✓	✓	-	-	✓	-	-	-	-
[15]	1	✓	✓	✓	✓	✓	✓	-	-	-
[16],[17]	1	✓	✓	✓	✓	✓	✓	-	-	-
[18]	1	✓	-	-	-	✓	-	-	-	-
[20]	1	-	✓	-	-	-	-	-	✓	-
[21]	2	-	-	✓	✓	-	-	-	✓	-
This work	1	✓	✓	✓	✓	✓	✓	✓	✓	✓

relevant information regarding the best expansion plan from an economic and environmental perspective. Different agents can use this information (e.g., system operator, DERs owners) to define the most suitable periods to make investments depending on their interests (e.g., environmental goals, financial limits). The proposed planning strategy assumes that: 1) The operation of the EDS is represented by a linearized AC model; 2) Short-term and long-term uncertainties are modeled through a set of discrete scenarios; 3) Environmental aspects are considered using the carbon tax; and 4) A set of planning periods indexed by p is considered.

The proposed DSEP problem, due to its characteristics, is inherently an MINLP problem. Thus, aiming to guarantee the optimality of the solution found, the original model is transformed into a MILP model, as in [17]. The MILP model is obtained using approximations and the piecewise linearization technique [22]. Such a model is solved via the CPLEX commercial solver, which ensures the solution's optimality by applying a branch-and-bound algorithm. Furthermore, two-stage stochastic programming fits the characteristics of the DSEP problem and is an effective method for dealing with scenario-based uncertainties.

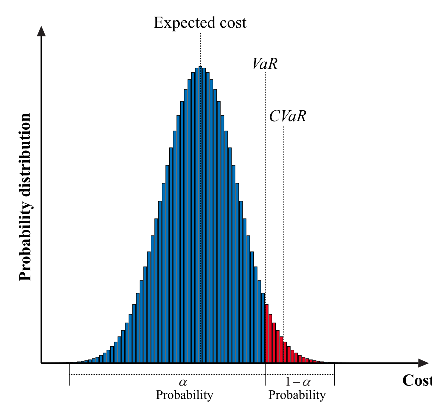

Fig. 1. CVaR and VaR representation.

A. Risk-Based Planning

The DSEP problem faces uncertainties related to the fluctuation of renewable generation, energy prices, demand growth, EV charging demand, among others. Therefore, it is essential to quantitatively assess the risk associated with planning decisions to obtain a more robust solution. The specialized literature has addressed risk-based planning [20], [21] mainly focused on operational costs and violations of technical restrictions. To the best of the authors' knowledge, the DSEP proposals have not considered risks related to environmental aspects. However, the modern DSEP must develop a low-carbon planning strategy to meet environmental goals and agreements (e.g., Paris Agreement). Thus, the main contribution of this work is to assess the risk from two perspectives, addressing both the risk traditionally considered in the literature (operational cost) and the risk related to environmental aspects (carbon tax), thus providing a balanced solution from an economic and environmental perspective. Risk-averse planning makes its decisions based on worst-case scenarios obtained from risk analysis. Therefore, CVaR [23] is adopted here to quantify the risk in the DSEP under uncertainties. This risk measure can be used in the planning problem to calculate the expected cost value for scenarios with the highest costs considering a certain probability of occurrence $(1-\alpha)\%$, for a given α (0, 1) [21]. Fig. 1 presents a graphic illustration of CVaR and value-at-risk (VaR) concepts. It can be noted that VaR represents the boundary between best and worst scenarios for the expected cost.

CVaR was chosen as a risk measure because of its efficiency and ease of implementation. In addition, CVaR has advantages over traditional risk measures, such as value at risk (VaR). Unlike the VaR risk measure, the CVaR is able to quantify the expectation of planning costs when these costs are greater than the VaR, identifying fat tails beyond the VaR. In addition, other alternatives, such as chance-constrained and robust optimization methods, can also be used to control risk in planning problems under uncertainties. Such methods have parameters that allow the generation of different solution proposals according to the factor of robustness/aversion defined for the problem. However, compared to these methods, the CVaR method has the advantage of providing an impact measure of the worst scenarios on the planning proposal; such measure is represented directly in the objective function of the problem. The other methods could minimize the maximum cost as an alternative to CVaR. Nonetheless, this practice is very conservative and does not provide information about the risk related to the tail scenarios (% of worst scenarios). Therefore, CVaR allows quantifying the impact of worst scenarios without adding binary variables as required by some implementations, e.g., the chance-constrained method [14], thus simplifying the problem-solving. Such a risk measure can be represented by convex and linear equations [24] that can be solved efficiently through linear programming, ensuring that the optimal solution to the problem is found. CVaR constrains the expected cost volatility related to planning decisions. Finally, to the authors' knowledge, there is no proposal for the DSEP problem that incorporates CVaR from two perspectives, defining a CVaR related to planning costs and another CVaR related to the carbon tax.

B. Objective Function

The objective function (1) adopted in this proposal aims to minimize the expected total cost (*TC*) including CVaR related to planning costs (CVaR^{pl}) and carbon tax (CVaR^{em}). The β^{pl} and β^{em} parameters are weights used to represent the compromise between expected cost and risk aversion, where $\beta^{pl/em} \in (0, 1)$. Therefore, if $\beta^{pl} = 1$ and $\beta^{em} = 1$ the problem is risk-averse and the model will optimize the CVaR related to both planning cost and carbon tax. On the other hand, if $\beta^{pl} = 0$ and $\beta^{em} = 0$, the problem will be risk neutral. Moreover, if necessary, the model allows optimizing only one of the risks (CVaR^{pl} or CVaR^{em}).

The risk measures related to planning costs and carbon taxes are determined by (2) and (3). Give a probability α, VaR^{pl} and VaR^{em} represent the boundary between best and worst scenarios for the planning cost and carbon tax, respectively; $\eta_s^{pl/em}$ are auxiliary variables used to calculate the $\text{CVaR}^{pl/em}$ as in [24]. Equation (4) determines the planning cost (PC) considering investment ($CINV$) and operational costs ($COPR$). Investment costs are determined by (5) and include investments in substations, lines, WT units, PV units, EVCSs, and ESSs, respectively. Operational costs are calculated by (6). The first term in (6) represents the energy supplied by substations; the second and third terms correspond to the operation and maintenance costs (O&M) of WT and PV units, respectively; the fourth and fifth terms represent the ESS operational costs. Finally, the carbon tax (CTX) is determined by (7). The function $f(\tau,\lambda) = (1-(1+\tau)^{-\lambda})/\tau$ is used to determine the present value of the annualized cost.

$$\min TC^{\text{RISK}} = PC + CTX + \beta^{pl}\text{CVaR}^{pl} + \beta^{em}\text{CVaR}^{em} \tag{1}$$

$$\text{CVaR}^{pl} = \text{VaR}^{pl} + \frac{1}{1-\alpha}\sum_s \pi_s \eta_s^{pl} \tag{2}$$

$$\text{CVaR}^{em} = \text{VaR}^{em} + \frac{1}{1-\alpha}\sum_s \pi_s \eta_s^{em} \tag{3}$$

$$PC = \left(\sum_p CINV_p + COPR_p\right)(1+\tau)^{-(p-1)\lambda} \tag{4}$$

$$\begin{aligned} CINV_p = {} & \sum_d C_d^{\text{S}} x_{,p}^{\text{S}} + \sum_{ij}\sum_a C_{ij,a}^{\text{L}} l_{ij} x_{ij,a,p}^{\text{L}} \\ & + \sum_k C_k^{\text{wt}} x_{k,p}^{\text{wt}} + \sum_u C_u^{\text{pv}} N_{u,p}^{\text{pv}} \\ & + \sum_r \sum_c C^{\text{INST}} x_{r,p}^{\text{EV}} + C_c^{\text{EV}} N_{r,c,p}^{\text{EV}} \\ & + \sum_b C_b^{\text{ES}} N_{b,p}^{\text{ES}} \end{aligned} \tag{5}$$

$$\begin{aligned} COPR_p = {} & \sum_s \pi_s d_s f(\tau,\lambda) \left(\sum_d C_s^{ep} P_{d,s,p}^{\text{s}} \right. \\ & + \sum_k C^{\text{op,wt}} P_{k,s,p}^{\text{wt}} + \sum_u C^{\text{op,pv}} P_{u,s,p}^{\text{pv}} \\ & \left. + \sum_b C^{\text{op,es}-} P_{b,s,p}^{\text{ES}-} + \sum_b C^{\text{op,es}+} P_{b,s,p}^{\text{ES}+} \right) \end{aligned} \tag{6}$$

$$CTX = \sum_p \sum_s \pi_s d_s f(\tau,\lambda) C_s^{em} \sum_i \zeta_i^{\text{s}} P_{i,s,p}^{\text{s}} \tag{7}$$

C. CVaR Constraints

The set of (8)–(10) represent the constraints related to the CVaR calculation. Constraints (8) and (9) link the $\text{VaR}^{pl}/\text{VaR}^{em}$ to the planning cost/carbon tax and the auxiliary variables n_s^{pl}/n_s^{em} in scenario *s*. Constraint (10) ensures that the auxiliary variables n_s^{pl}/n_s^{em} are nonnegative.

$$c_s^{pl} - n_s^{pl} - \text{VaR}^{pl} \leq 0 \qquad \forall s \tag{8}$$

$$c_s^{em} - n_s^{em} - \text{VaR}^{em} \leq 0 \qquad \forall s \tag{9}$$

$$n_s^{pl}, n_s^{em} \geq 0 \qquad \forall s \tag{10}$$

In (8)–(10), c_s^{pl} and c_s^{em} represent the expected planning cost and the expected carbon tax in scenario *s*; n_s^{pl} is an auxiliary continuous variable that measures the difference between the planning cost and VaR^{pl} in scenario *s*; n_s^{em} is an auxiliary continuous variable that measures the difference between the carbon tax and VaR^{em} in scenario *s*. Note that for any scenario that $\text{VaR}^{pl}/\text{VaR}^{em}$ is higher than the planning cost/carbon tax n_s^{pl}/n_s^{em} will be zero.

D. Steady-State Operation Constraints

The set of expressions (11)–(14) represents the steady-state operation of the distribution system. The power balance is represented by (11) and (12). Constraints (13) and (14) represent application of Kirchhoff's second law and the linearization of current calculation. The model is originally nonlinear. For this reason, the piecewise method is used here to linearize the model. Thus, the piecewise f-function is defined to calculate the sum of $(\hat{P}_{ij,s,p})^2 + (\hat{Q}_{ij,s,p})^2$, using Γ blocks. Details of this linearization are described in [22].

Auxiliary constraint (15) relates the current, power flow (active and reactive) with the selection of conductor a for the line *ij*.

$$\sum_{ji}\sum_{a} P_{ji,a,s,p} - \sum_{ij}\sum_{a}(P_{ij,a,s,p} + R_a l_{ij} I^{\text{sqr}}_{ij,a,s,p}) + P^{\text{s}}_{i,s,p}$$
$$+ P^{\text{wt}}_{i,s,p} + P^{\text{pv}}_{i,s,p} + P^{\text{ESD}}_{i,s,p} - P^{\text{ESC}}_{i,s,p}$$
$$= P^{D}_{i,p} f^{\text{D}}_{s,p} + D^{EVS}_{i,s,p}; \qquad \forall i,\ s, p \qquad (11)$$

$$\sum_{ki}\sum_{a} Q_{ki,a,s,p} - \sum_{ij}\sum_{a}(Q_{ij,a,s,p} + X_a l_{ij} I^{\text{sqr}}_{ij,a,s,p})$$
$$+ Q^{\text{s}}_{s,s,p} + Q^{\text{wt}}_{k,s,p} + Q^{\text{pv}}_{u,s,p} = Q^{\text{D}}_{i,p} f^{\text{D}}_{s,p}; \qquad \forall i, s, p \qquad (12)$$

$$V^{\text{sqr}}_{i,s,p} - V^{\text{sqr}}_{j,s,p} = \sum_{a}[2\left(R_a P_{ij,a,s,p} + X_a Q_{ij,a,s,p}\right) l_{ij}$$
$$+ Z^2_a l^2_{ij} I^{\text{sqr}}_{ij,a,s,p}] + b_{ij,s,p}; \qquad \forall ij,\ s,\ p \qquad (13)$$

$$V^{\text{sqr}}_{j,s,p} \hat{I}^{\text{sqr}}_{ij,s,p} = f\left(P_{ij,s,p},\ \Gamma\right) + f\left(Q_{ij,s,p},\ \Gamma\right); \quad \forall ij,\ s,\ p \qquad (14)$$

$$\hat{I}^{\text{sqr}}_{ij,s,t} = \sum_{a} I^{\text{sqr}}_{ij,a,s,p}; \hat{P}_{ij,s,t} = \sum_{a} P_{ij,a,s,p}\ ; \hat{Q}_{ij,s,t}$$
$$= \sum_{a} Q_{ij,a,s,p}\ ; \qquad \forall ij,\ s,\ p \qquad (15)$$

E. Operational Constraints

The EDS operational limits are established by the set of (16)–(24). Voltages at buses and current through lines are limited by (16) and (17), respectively. Constraint (18) defines the active and reactive power flow limits through line ij. Moreover, the limits for current, active and reactive power flow are ensured by the set of (19)–(21), respectively. The square of the apparent power ($\varrho^{\text{sqr}}_{d,s,p}$) provided by the substation is calculated in (22) and restricted by (23). Variable $b_{ij,s,p}$ is used in (13) to ensure the feasibility of the problem in case line ij is not installed. Such variable is limited by (24); if the line ij is operating then $b_{ij,s,p} = 0$, otherwise, $b_{ij,s,p}$ can take any value restricted by $\bar{b}$. Besides that, constraint (25) relates the flow direction binary variables $(\psi^{+}_{ij,p} + \psi^{-}_{ij,p})$ the operation variable ($z_{ij,a,p}$) for each line ij. Therefore, if $\psi^{+}_{ij,p}$ or $\psi^{-}_{ij,p}$ is equal to 0, then the line *ij* is not operating. Otherwise, if $\psi^{+}_{ij,p}$ or $\psi^{-}_{ij,p}$ is equal to 1, then the line *ij* is in operation. The binary variables $\psi^{+}_{ij,p}$, $\psi^{-}_{ij,p}$ indicate the flow direction in each line. Thus, if $\psi^{+}_{ij,p} = 1$ and $\psi^{-}_{ij,p} = 0$, then the flow direction is from bus *i* to bus *j*. On the other hand, if $\psi^{+}_{ij,p} = 0$ and $\psi^{-}_{ij,p} = 1$ the flow direction is from bus *j* bus *i*.

$$\underline{V}^2 \leq V^{\text{sqr}}_{i,s,p} \leq \overline{V^2}; \qquad \forall i,\ s, p \qquad (16)$$

$$0 \leq I^{\text{sqr}}_{ij,a,s} \leq \overline{I^2_a} z_{ij,a,p}; \qquad \forall ij, a,\ s,\ p \qquad (17)$$

$$|P_{ij,a,s,p}| \leq \overline{VI_a} z_{ij,a,p};\ |Q_{ij,a,s,p}|$$
$$\leq \overline{VI_a} z_{ij,a,p}; \qquad \forall ij, a,\ s,\ p \qquad (18)$$

$$0 \leq I^{\text{sqr}}_{ij,a,s,p} \leq \overline{I^2_a}\left(\psi^{+}_{ij,p} + \psi^{-}_{ij,p}\right); \qquad \forall ij, a,\ s,\ p \qquad (19)$$

$$|P_{ij,a,s,p}| \leq \overline{VI_a}\left(\psi^{+}_{ij,p} + \psi^{-}_{ij,p}\right); \qquad \forall ij, a,\ s,\ p \qquad (20)$$

$$|Q_{ij,a,s,p}| \leq \overline{VI_a}\left(\psi^{+}_{ij,p} + \psi^{-}_{ij,p}\right); \qquad \forall ij, a,\ s,\ p \qquad (21)$$

$$\varrho^{\text{sqr}}_{d,s,p} = \left(P^{\text{s}}_{d,s,p},\ \ Q^{\text{s}}_{d,s,p}, \Gamma\right); \qquad \forall d,\ s, p \qquad (22)$$

$$\varrho^{\text{sqr}}_{d,s,p} \leq \left(\varrho^{i}_{d}\right)^2$$
$$+ \sum_{t=1}^{P}\left(2\varrho^{i}_{d}\varrho^{f}_{d} + {\varrho^{i}_{d}}^2\right) x^{\text{S}}_{d,p}; \qquad \forall d,\ s, p \qquad (23)$$

$$|b_{ij,s,p}| \leq \bar{b}\left(1 - \psi^{+}_{ij,p} - \psi^{-}_{ij,p}\right); \qquad \forall ij,\ s,\ p \qquad (24)$$

$$\psi^{+}_{ij,p} + \psi^{-}_{ij,p} = \sum_{a} z_{ij,a,p}; \qquad \forall ij, p \qquad (25)$$

F. Constraints of Investments in Lines and Substations

The set of (26)–(28) represents the constraints related to investments in substations and lines. Constraint (26) ensures that each line will only be used if a previous investment has been made in it. Constraints (27) and (28) limit the investment in lines and substations over the planning horizon.

$$z_{ij,a,p} = \sum_{t=1}^{P} x^{L}_{ij,a,t}; \qquad \forall ij, a, p \qquad (26)$$

$$\sum_{p}\sum_{a} x^{\text{L}}_{ij,a,p} \leq 1; \qquad \forall ij \qquad (27)$$

$$\sum_{p} x^{\text{S}}_{d,p} \leq 1; \qquad \forall d \qquad (28)$$

G. Constraints of Investments in Renewable DG Units

The (29)–(34) represent the investment and operational limits of renewable DG units. Constraint (29) ensures that only one wind generator unit will be installed at each bus, while (30) limits the quantity of PV technologies can be allocated at each bus throughout the planning. Moreover, the operational limits of active/reactive power by renewable DG units are presented in (31)–(32) for WT units, and (33)–(34) for PV units.

$$\sum_{p} x^{\text{wt}}_{k,p} \leq 1; \qquad \forall k \qquad (29)$$

$$\sum_{p} N^{\text{pv}}_{u,p} \leq \bar{N}^{\text{pv}}_{u}; \qquad \forall u \qquad (30)$$

$$0 \leq P^{\text{wt}}_{k,s,p} \leq f^{\text{wt}}_{s} \bar{P}^{\text{wt}}_{k} \sum_{t=1}^{P} x^{\text{wt}}_{k,p}; \qquad \forall k, s, p \qquad (31)$$

$$\left|Q^{\text{wt}}_{k,s,p}\right| \leq P^{\text{wt}}_{k,s,p} \tan\left(\cos^{-1}\left(\varphi^{\text{wt}}\right)\right); \qquad \forall k, s, p \qquad (32)$$

$$0 \leq P^{\text{pv}}_{u,s,p} \leq f^{\text{pv}}_{s} \bar{P}^{\text{pv}}_{u} \sum_{t=1}^{P} N^{\text{pv}}_{u,p}\ ; \qquad \forall u,\ s, p \qquad (33)$$

$$\left|Q^{\text{pv}}_{u,s,p}\right| \leq P^{\text{pv}}_{u,s,p} \tan\left(\cos^{-1}\left(\varphi^{\text{pv}}\right)\right); \qquad \forall u,\ s, p \qquad (34)$$

H. Constraints of Investments in EVCSs

A centralized strategy for the planning of distribution system and EVCSs has been considered in this work, which is widely assumed for the long-term planning due to the complexity of this problem [16], [17]. Constraint (35) guarantees that for each bus only one charging station is installed. Equation (36) restricts the quantity of EV chargers allocated at each bus. Constraint (37) guarantees that the EV charging demand in EVCSs does not surpass the maximum capacity of the EVCSs. Furthermore, (38) establishes that the demand in charging stations coincides to the EV demand.

$$\sum_{p} x^{\mathrm{EV}}_{r,p} \leq 1; \qquad \forall r \qquad (35)$$

$$\sum_{p} N^{\mathrm{EV}}_{r,c,p} \leq \bar{N}^{\mathrm{EV}}_{c}; \qquad \forall r, c \qquad (36)$$

$$D^{\mathrm{EVCS}}_{r,s,p} \leq \sum_{t=1}^{P} N^{\mathrm{EV}}_{r,c,t} P^{\mathrm{EV}}_{c}; \qquad \forall r, c, s, p \qquad (37)$$

$$\sum_{r} D^{\mathrm{EVCS}}_{r,s,p} = D^{\mathrm{EV}}_{s,p} \qquad \forall r, s, p \qquad (38)$$

I. Constraints of Investments in ESS

Constraint (39) limits the quantity of ESS that can be allocated at each bus during the entire planning period. In addition, (40) and (41) limit the charging and discharging power in an ESS according to the capacity of the converter. Finally, as in [25], (42) is used to represent an approximation of the charging and discharging processes of an battery bank in each time block ϖ.

$$\sum_{p} N^{\mathrm{ES}}_{b,p} \leq \bar{N}^{\mathrm{ES}}_{b}; \qquad \forall b \qquad (39)$$

$$0 \leq P^{\mathrm{ES}-}_{b,s,p} \leq \sum_{t=1}^{P} P^{\mathrm{ES}}_{b} N^{\mathrm{ES}}_{b,p}; \qquad \forall b,\ s, p \qquad (40)$$

$$0 \leq P^{\mathrm{ES}+}_{b,s,p} \leq \sum_{t=1}^{P} P^{\mathrm{ES}}_{b} N^{\mathrm{ES}}_{b,p}; \qquad \forall b, s, p \qquad (41)$$

$$\sum_{s^{\varpi}} d_s \left(\eta^{\mathrm{ES}-} P^{\mathrm{ES}-}_{b,s,p} - \frac{1}{\eta^{\mathrm{ES}+}} P^{\mathrm{ES}+}_{b,s,p}\right) = 0; \qquad \forall b,\ bl, p \qquad (42)$$

J. Radiality Constraints

Constraints (43)–(45), along with (14) and (15), ensure the radial operation of the distribution network. Thus, (43) establishes that branches connected to substation will always operate in the forward direction. Moreover, (44) determines that each demand bus must be connected to only one line in the forward direction. Finally, (45) permits the use of connection buses (i.e., buses without demand that can be used as connecting buses for demand buses) [26].

$$\sum_{ij} \psi^{-}_{ij,p} + \sum_{ki} \psi^{+}_{ki,p} = 0; \qquad \forall i, p | i \in S \qquad (43)$$

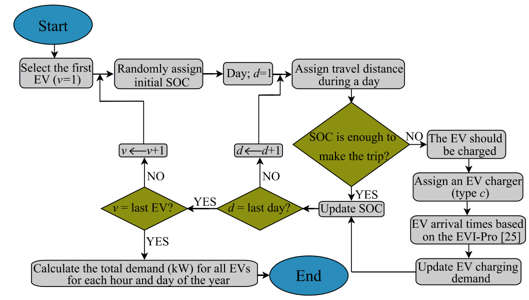

Fig. 2. Method to determine EV charging demand.

$$\sum_{ij} \psi^{-}_{ij,p} + \sum_{ki} \psi^{+}_{ki,p} = 1; \qquad \forall i,\ p | P^{\mathrm{D}}_{i,p,s} > 0 \qquad (44)$$

$$\sum_{ij} \psi^{-}_{ij,p} + \sum_{ki} \psi^{+}_{ki,p} \leq 1; \qquad \forall i,\ t \left| P^{\mathrm{D}}_{i,p,s} = 0 \right| i \notin S \qquad (45)$$

K. Uncertainty Modeling

Short-term uncertainties are related to variability of renewable generation (PV and WT units), wind speed, conventional demand, EV demand, and energy price. On the other hand, long-term uncertainties are associated with demand growth and carbon tax per planning period. The choice of long-term uncertain parameters depends on aspects related to the type of problem (nature, size), problem objective, time to find a solution and its quality (feasible, local optimal, or global optimal). There are many long-term uncertainties in the DSEP associated with storage, grid access, DG penetration, demand, and carbon tax, among others. However, due to the high complexity and elevated computational cost of the planning problem, only two long-term uncertainties were chosen, thus guaranteeing the scalability of the proposed model. The specific choice of uncertainties related to demand growth and the carbon tax is due to the characteristics and focus of the problem addressed in this work. Since demand growth significantly impacts planning decisions, representation of these uncertainties is crucial to obtain a solution that is more committed to reality. In addition, the problem addressed also focuses on environmental aspects, aiming to obtain a low-carbon planning strategy [27]. Hence, the uncertainty related to the carbon tax was chosen to represent the environmental issues. Uncertainties are modeled through discrete scenarios using historical data for conventional demand, solar irradiance, and wind speed. The uncertainty associated with EV demand is modeled using the algorithm presented in [17]. A summary of the method used to determine EV charging demand is illustrated in Fig. 2. The k-means clustering method [28] reduces the number of scenarios related to short-term uncertainties. This method uses historical data of uncertain parameters as input data, providing as output a reduced set of scenarios related to conventional demand, EV demand, wind speed, and solar irradiation.

Considering that uncertain variables have a correlation due to seasonality and dependences of solar irradiation and wind speed, it is important to highlight that the application of the k-means method for data clustering and scenario reduction maintains such correlation between the uncertain data, as indicated in reference

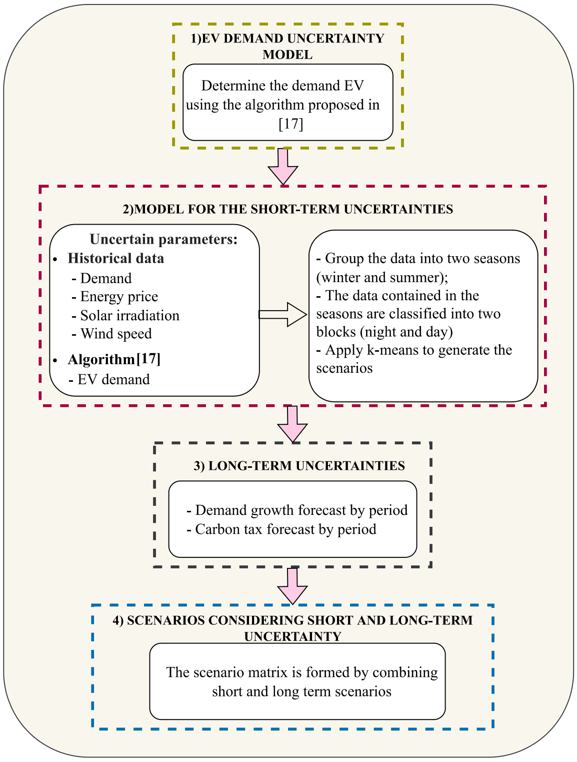

Fig. 3. Scenario generation process.

TABLE II
LONG-TERM SCENARIOS

Scenarios	Annual demand growth (%) [30]	Annual carbon tax growth (%) [31]
Low	3.2%	1%
Moderate	3.8%	4%
High	4.4%	5%

[29]. This method has been widely used in the DSEP problem [9], [15]. Both short- and long-term scenarios are combined obtaining the scenarios used in the proposed model. The data used for the long-term uncertainties are obtained using the demand growth forecast from [30] and the carbon energy tax forecast from [31]. Fig. 3 illustrates the uncertainty modeling process in this work. Table II shows the three demand growth scenarios and carbon tax classified as low, moderate, and high, which have the same probability of occurrence. Finally, a summary of the uncertainty modeling is described as follows:

i) First, scenarios related to short-term (SST), and long-term (SLT) uncertainties are defined.
ii) Short-term uncertainties are based on historical data over one year. Such data are classified into two seasons: winter and summer (time blocks). The time blocks are categorized into two sub-blocks (day and night) to represent the variation of generation and demand, mainly the photovoltaic generation that generates power during the day and does not generate it at night.
iii) The k-means clustering technique is applied to cluster the data of each sub-block into clusters k, providing reduced scenarios.
iv) At the end of the process, a set of 32 scenarios is obtained (2 seasons $\times$ 2 sub-blocks $\times$ 8 clusters) that represent the short-term uncertainties. Such uncertainties are related to the hourly behavior of solar irradiation, wind speed, conventional demand, and EV demand over a year.
v) The probabilities for each scenario are determined by dividing the time (hours) in the respective scenario by the sum of the hours of all scenarios. The SLT are obtained using data from studies that perform projections for the growth of demand [30] and carbon tax [31]. Finally, operation scenarios are formed by combining SST with SLT, obtaining 96 scenarios (32 SST x 3 SLT).

The historical data are divided into two seasons (winter and summer), considering the characteristics of a tropical country like Brazil. Therefore, the seasons are grouped into spring/summer (summer) and autumn/winter (winter). Such consideration does not compromise the quality of the solutions since, in Brazil, there is no significant divergence between the spring/summer and autumn/winter seasons. Furthermore, such a model can be easily adapted to deal with the characteristics of other countries. The representation of uncertainties through discrete scenarios aims to obtain a trade-off between the representation of uncertainty and computational tractability. Such an approach has been widely adopted in the specialized literature [5], [6], [7].

III. TESTS AND RESULTS

The proposed model has been written in AMPL and solved using CPLEX. To address the uncertainties, a set of 96 scenarios considering long and short-term uncertainties is used. The operational cost of EVCSs corresponds to 10% of the investment cost in these technologies, as done in [14]. The proposed model was validated using the 24 and the 54-bus EDS. Data related to the DG units, EVCSs, ESS, short-term scenarios, long-term scenarios, among others, are available in [32].

A. 24-Bus EDS

A 24-bus distribution network [17] is used to evaluate the strategy proposed. Such system has the following specifications: voltage 20 kV; 20 load buses; 2 existing substations; 2 candidate buses for constructing new substations. The horizon is 10 years, separated into two periods of 5-years each. An investment limit of $70 million is assumed.

Four case studies are analyzed: 1) A risk-neutral strategy for the planning of EDS and EVCSs; 2) A risk-averse strategy considering CVaR related to planning cost; 3) A risk-averse strategy considering CVaR related to carbon tax; 4) A risk-averse strategy from two perspectives: planning costs and carbon taxes. In this work, α is considered 0.95, therefore, the set of worst scenarios has a probability of occurrence of 5%.

1) Risk-Neutral Strategy for the Planning of EDS and EVCSs (Case 1): Risk-neutral strategy (Case 1) makes decisions based on the expected value of the objective function without considering the risks related to the planning decisions. Such a strategy provides an optimal solution with the expected cost of $150.16

million. The proposed planning makes the following decisions: Period 1: installation of substations 23 and 24, investments in charging stations with 1 charger of 50 kW and 3 of 150 kW at buses 4, 10, 13, 14, and 15, installation of 6 WT units at buses 3, 5, 9, 11, 16, and 19, allocation of 338 PV units (23 at bus 3, 14 at bus 4, 20 at bus 6, 54 at bus 8, 9 at bus 10, 110 at bus 12, 22 at bus 13, and 85 at bus 14), and installation of 15 new lines. Period 2: installation of 6 PV units (3 at buses 8 and 13) and 1 ESS at bus 8.

2) Risk-Averse Strategy Considering CVaR Related to Planning Cost (Case 2): In contrast to the risk-neutral strategy, the risk-averse strategy makes decisions based on worst scenarios using the risk measure CVaR, specifically the risk tool is associated with the planning cost (CVaR^{pl}). In this strategy, the total cost of planning is $160.19 million. The proposed planning determines these actions: Period 1: installation of substations at buses 23 and 24, installation of EVCSs with 1 charger of 50 kW and 3 of 150 kW for the buses 4, 10, 13, 14, and 15, installation of 6 WT units at buses 3, 5, 9, 11, 16, and 19, installation of 191 PV units (13 at bus 3, 12 at bus 6, 25 at bus 8, 16 at bus 10, 60 at bus 12, 11 at bus 13, and 54 at bus 14), and installation of 15 new lines. Period 2: Allocation of 13 PV units (5 at bus 8 and 8 at bus 12).

3) Risk-Averse Strategy Considering CVaR Related to Carbon Tax (Case 3): This case only considers CVaR related to carbon tax. The cost of the proposed planning is $162.45 million. This strategy makes the following decisions: Period 1: installation of substations at buses 23 and 24, installation of EVCSs with 1 charger of 50 kW and 3 of 150 kW for the following buses 4, 10, 13, 14, and 15, installation of 6 WT units at buses 3, 5, 9, 11, 16, and 19, allocation of 554 PV units (25 at bus 3, 26 at bus 6, 85 at bus 8, 26 at bus 10, 211 at bus 12, 29 at bus 13, and 152 at bus 14), and installation of 15 new lines. Period 2: Installation of 23 PV units (4 at bus 3, 3 at bus 6, 11 at bus 10, and 5 at bus 13).

4) Risk-Averse Strategy From Two Perspectives: Planning Costs and Carbon Tax (Case 4): This case considers a risk-averse strategy from two perspectives: planning costs and carbon tax. The cost of the proposed planning is $153.62 million. The investment plan establishes the following actions: Period 1: installation of substations at buses 23 and 24, allocation of EVCSs with 1 charger of 50 kW and 3 chargers of 150 kW at buses 4, 10, 13, 14, and 15, installation of 6 WT units at buses 3, 5, 9, 11, 16, and 19, 264 PV units (16 at bus 3, 17 at bus 6, 45 at bus 8, 19 at bus 10, 82 at bus 12, 19 at bus 13, and 66 at bus 14), and installation of 15 new lines. Period 2: Installation of 4 PV units at bus 10.

5) Analysis and Comparison of Results: A summary of the main planning results for Cases 1, 2, 3, and 4 is shown in Table III. Risk-neutral strategy (Case 1) offers an expected cost about 6.26%, 7.57%, and 2.25% lower than Cases 2, 3, and 4, respectively. However, this strategy increases the risks related to planning decisions. Note that in this case the cost of the sum $\text{CVaR}^{pl} + \text{CVaR}^{em}$ increases by about 6.43%, 0.03%, and 6.59% when compared to Cases 2, 3, and 4 respectively. Therefore, the strategy averse to both the planning cost and carbon tax risks presented the best results in relation to $\text{CVaR}^{total}(\text{CVaR}^{pl} + \text{CVaR}^{em})$. Moreover, Case 2 presents the lowest CVaR related to planning cost, with a difference of 7.80%, 12.03%, and 2.20% when compared to Cases 1, 3, and 4, respectively. Moreover, Case 3 obtained the lowest CVaR related to carbon tax with a difference of 9.93%, 6.62%, and 0.65% when compared to cases 1, 2, and 4, respectively.

TABLE III
RESULTS OF THE PROPOSED PLANNING FOR CASES 1, 2, 3, AND 4

Case	**1**	**2**	**3**	**4**
Investment costs (millions of USD)				
Substations	6.00	6.00	6.00	6.00
Lines	1.23	1.25	1.24	1.24
WT units	24.00	24.00	24.00	24.00
PV units	20.44	12.24	34.10	15.99
EVCSs	1.58	1.58	1.58	1.58
ESS	0.21	3.09	3.09	3.09
Total investment	53.46	48.16	70.00	51.89
Operational costs (millions of USD)				
Energy purchased	60.37	69.69	57.25	63.14
DER units O&M	0.47	0.93	1.41	1.17
Total operational	60.84	70.62	58.66	64.31
Carbon tax	35.86	41.41	33.78	37.42
Total cost	150.16	160.19	162.45	153.62
Risk measure (millions of USD)				
CVaR^{pl}	202.81	188.13	210.77	192.27
CVaR^{em}	88.98	86.30	80.94	81.47
$\text{CVaR}^{pl} + \text{CVaR}^{em}$	291.79	274.43	291.71	273.74
CO_2 emissions (ktons)	338.09	390.28	320.61	353.56
Computational time (h)	3.95	2.08	1.02	2.59

An important point to be highlighted in Table III is that the strategies based on risk invested almost 15 times more in ESS than the risk-neutral strategy. In addition, Case 2, which consider the risk related to the planning cost, invested less in PV units due to the high impact of the uncertainties related to this technology. On the other hand, Case 3, which only considers the risk associated with the carbon tax, is the case that most invested in PV units (see Table III). Moreover, Cases 2 and 4, which address the risk related to the planning cost, are the cases that buy more energy from the grid since it comes from dispatchable sources and there are no uncertainties associated with energy production.

Table IV highlights the differences between investments for Cases 1, 2, 3, and 4. Investments in EVCSs, WT units, and substations for both cases are the same. The differences in expansion plans for each case are related to investments in PV units, ESS, and some lines, as shown in Table IV. Note that Case 3 invested more in PV units than the other cases. In addition, Cases 2, 3, and 4, that address risk, invested more in ESS. Case 1 installed only one ESS at bus 8 and planning period 2. On the other hand, Cases based on risk (2, 3, and 4) installed 9 ESS at buses 3, 4, 6, 8, 10, 13, 14, 15, and 19 in the planning period 1. Another difference between the expansion plans for the case studies is related to the investment in lines. For example,

TABLE IV
DIFFERENCES BETWEEN INVESTMENTS FOR CASES 1, 2, 3, AND 4

	Case 1	**Case 2**	**Case 3**	**Case 4**
PV units (bus *i*, units, period *p*)	3,23,1; 4,14,1; 6,20,1; 8,54,1; 8,3,2; 10,9,1; 12,110,1; 13, 22, 1; 13, 3,2; 14,85,1;	3,13,1; 6,12,1; 8,25,1; 8,5,2; 10,16,1; 12,60,1; 12,8,2; 13, 11, 1; 14,54,1;	3,25,1; 3,4,2; 6,23,1; 6,3,2; 8,85,1; 10,26,1; 10,11,2; 12,211,1; 13, 29, 1; 13, 5,2; 14,152,1;	3,16,1; 6,17,1; 8,45,1; 10,19,1; 10,4,2 12,82,1; 13,19,1; 14,66,1;
ESS (bus *i*, period *p*)	8,2;	3,1; 4,1; 6,1;8,1; 10,1; 13,1; 14,1; 15,1; 19,1;	3,1; 4,1; 6,1;8,1; 10,1; 13,1; 14,1; 15,1; 19,1;	3,1; 4,1; 6,1;8,1; 10,1; 13,1; 14,1; 15,1; 19,1;
Lines (branch *ij*,	3–16; 6–13;	10–23; 11–23;	6–13; 7–11;	6–13; 7–11;

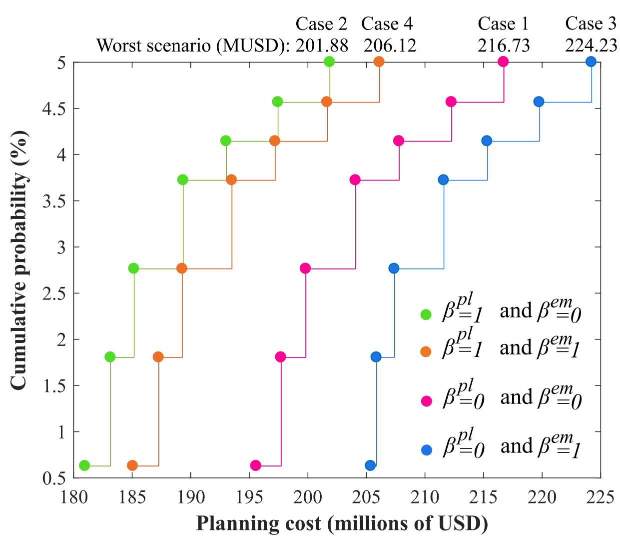

Fig. 4. Comparison of planning cost for worst case scenarios in cases 1, 2, 3, and 4.

in contrast to the other cases (2, 3, and 4), Case 1 installed line 3–16, while Cases 2, 3, and 4 installed line 10–23. Furthermore, Case 2 is the only one that invested in the construction of lines 11–23 and 20–24.

Fig. 4 presents a comparison between the worst scenarios related to the planning cost for Cases 1, 2, 3, and 4. Note that Case 3, which considers only the risk related to the carbon tax (CVaR^{em}), has higher planning costs in the worst scenario reaching a planning cost of \$224.23 million. In contrast to Case 3, Case 2, which addresses the CVaR^{pl}, has the lowest planning cost in the worst-case scenario with about \$201.88 million, representing a reduction of 6.85%, 10.17%, and 2.06% when compared to Cases 1, 3, and 4.

Fig. 5 illustrates the comparison between the worst scenarios related to the carbon tax for cases 1, 2, 3 and 4. Risk-neutral strategy (Case 1) had higher carbon tax-related costs with an increment of approximately 2.63%, 9.92%, and 9.55% compared to Cases 2, 3, and 4. Finally, by adding the planning costs and

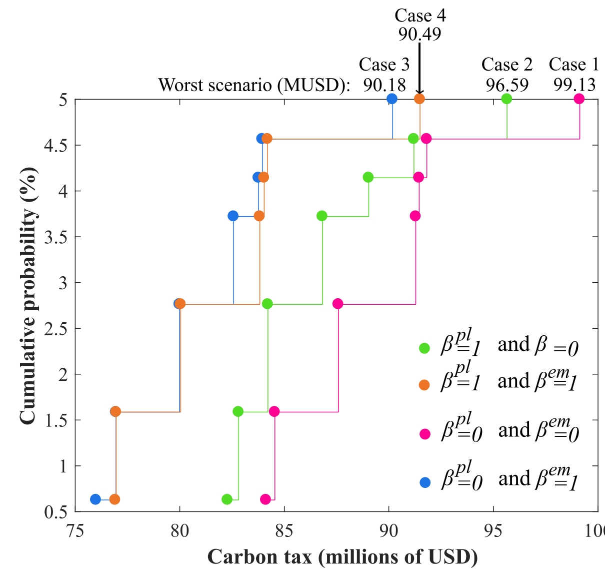

Fig. 5. Comparison of carbon tax for worst case scenarios in cases 1, 2, 3, and 4.

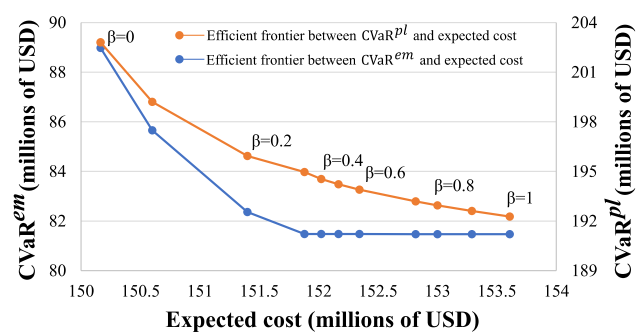

Fig. 6. Efficient frontier (24-bus EDS).

carbon tax in the worst scenario, the following costs (millions of USD) for each case are obtained: 315.86 (Case 1), 298.47 (Case 2), 314.41 (Case 3), 296.61 (Case 4). Note that Case 4, which is the case that considers both risks (planning cost and carbon tax), had the lowest total cost in the worst scenario of about 6.09%, 0.62%, and 5.66% less than cases 1, 2, and 3, respectively. Therefore, if the decision maker chooses the risk-averse strategy (Case 4) and the worst scenario occurs, there will be an economy of about \$19 million in total cost when compared to the risk-neutral planning strategy (Case 1).

Fig. 6 shows a sensitivity analysis with different β. For this test it was considered that $\beta = \beta^{pl} = \beta^{em}$. This figure illustrates how the variation of β impacts the CVaR^{pl}/CVaR^{em} and expected cost. Thus, it can be concluded that the increase in β leads to a decrease in CVaR^{pl}/CVaR^{em} and an increase in expected cost. Note that from $\beta = 0.3$, CVaR^{em} becomes stable and practically does not change its value. More details regarding the sensitivity analysis are provided in Table V, showing the difference (%) between the risk-neutral solution ($\beta = 0$) and the solutions that addresses the risk ($\beta > 0$) regarding the sum of the expected value and CVaR^{total}. Such solutions can be used by

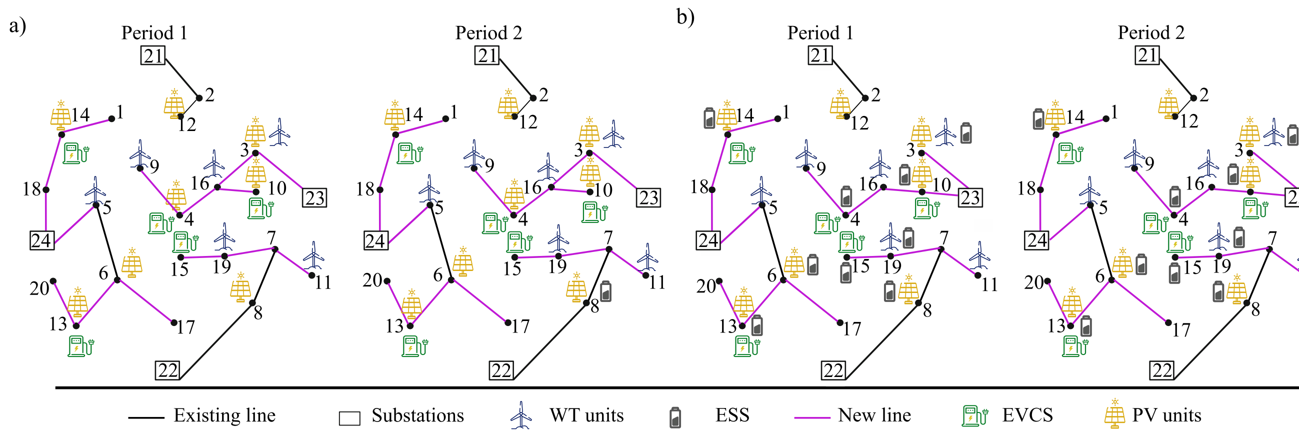

Fig. 7. Topology for the 24-node EDS: (a) Case 1; (b) Case 4.

TABLE V
SENSITIVITY ANALYSIS FOR DIFFERENT β

β	Expected cost	CVaR^{pl}	CVaR^{em}	EXC (%)	CVaR^{total} (%)
0	150.16	202.81	88.98	---	---
0.1	150.60	199.21	85.66	0.29	2.37
0.2	151.40	195.93	82.36	0.82	4.63
0.3	151.88	194.96	81.47	1.14	5.26
0.4	152.02	194.54	81.47	1.24	5.41
0.5	152.17	194.22	81.47	1.33	5.52
0.6	152.34	193.90	81.47	1.45	5.63
0.7	152.82	193.19	81.47	1.77	5.87
0.8	153.00	192.95	81.47	1.89	5.95
0.9	153.29	192.61	81.47	2.08	6.07
1.0	153.61	192.27	81.47	2.29	6.19

the decision-maker according to his needs and priorities (e.g., carbon tax, budget limits). Finally, Fig. 7 presents the system topology for the risk-neutral case (Case 1) and the case that addresses both risks (planning cost and carbon tax) (Case 4). One of the main differences between the topologies proposed for Case 1 and 4 is the divergence in ESS investments. Case 1 invested in only one ESS in the second planning period (see Fig. 7). On the other hand, Case 4 installs 9 ESS in the first planning period. Furthermore, differences in the circuits built between Cases 1 and 4 can be observed in Fig. 7. For example, unlike Case 4, Case 1 builds circuit 3-16.

B. 54-Bus EDS

The 54-bus EDS was adapted from [7] and used to validate the scalability of the proposed model. This system contains 50 load buses and four substations, two existing (buses 51 and 52) and two that can be built (buses 53 and 54). The nominal voltage of this system is 13.5 kV, and the maximum and minimum voltage limits are set at 1.05 and 0.95 p.u., respectively. The horizon is 10 years, separated into two periods of 5 years each. Data from this system are available in [32]. Finally, the proposed model was applied to a 54-bus EDS considering the risk-neutral and risk-averse problem.

TABLE VI
RESULTS OF THE PROPOSED PLANNING APPLIED TO THE 54-BUS EDS

Case	Risk-neutral	Risk-averse
Investment costs (millions of USD)		
Substations	6.00	6.00
Lines	1.56	1.46
WT units	19.80	19.80
PV units	20.52	14.68
EVCSs	1.61	1.61
ESS	0.43	3.43
Total investment	49.92	46.99
Operational costs (millions of USD)		
Energy purchased	169.94	175.23
DER units O&M	0.69	1.49
Total operational	170.64	176.72
Carbon tax	100.89	103.92
Total cost	321.45	327.63
Risk measure (millions of USD)		
CVaR^{pl}	351.63	338.75
CVaR^{em}	179.79	171.46
CVaR^{pl} + CVaR^{em}	531.42	510.21
Worst scenarios (millions of USD)		
Planning cost	378.23	365.54
Carbon tax	199.23	191.00
Total cost	577.46	556.54

The main planning results are described in Table VI. Expected cost for the risk-neutral problem was around 1.89% lower than the risk-averse problem. Nonetheless, the risk-averse problem obtained the best results concerning the risk measure. This strategy provides costs of CVaR^{pl}, CVaR^{em}, CVaR^{total} (CVaR^{pl} + CVaR^{em}), about 3.66%, 4.63%, and 3.99% lower than the risk-neutral problem. As can be seen in Table VI, if the worst-case scenario occurs and the decision maker chooses the risk-averse strategy, it can save about \$20.92 million in total cost compared to the risk-neutral planning strategy. This result is similar to the one obtained by the proposed model using the 24-bus distribution system. Furthermore, the main investment differences between the risk-neutral and risk-averse problems are related to PV units and ESSs. The risk-averse versus risk-neutral strategy invests more in ESSs and

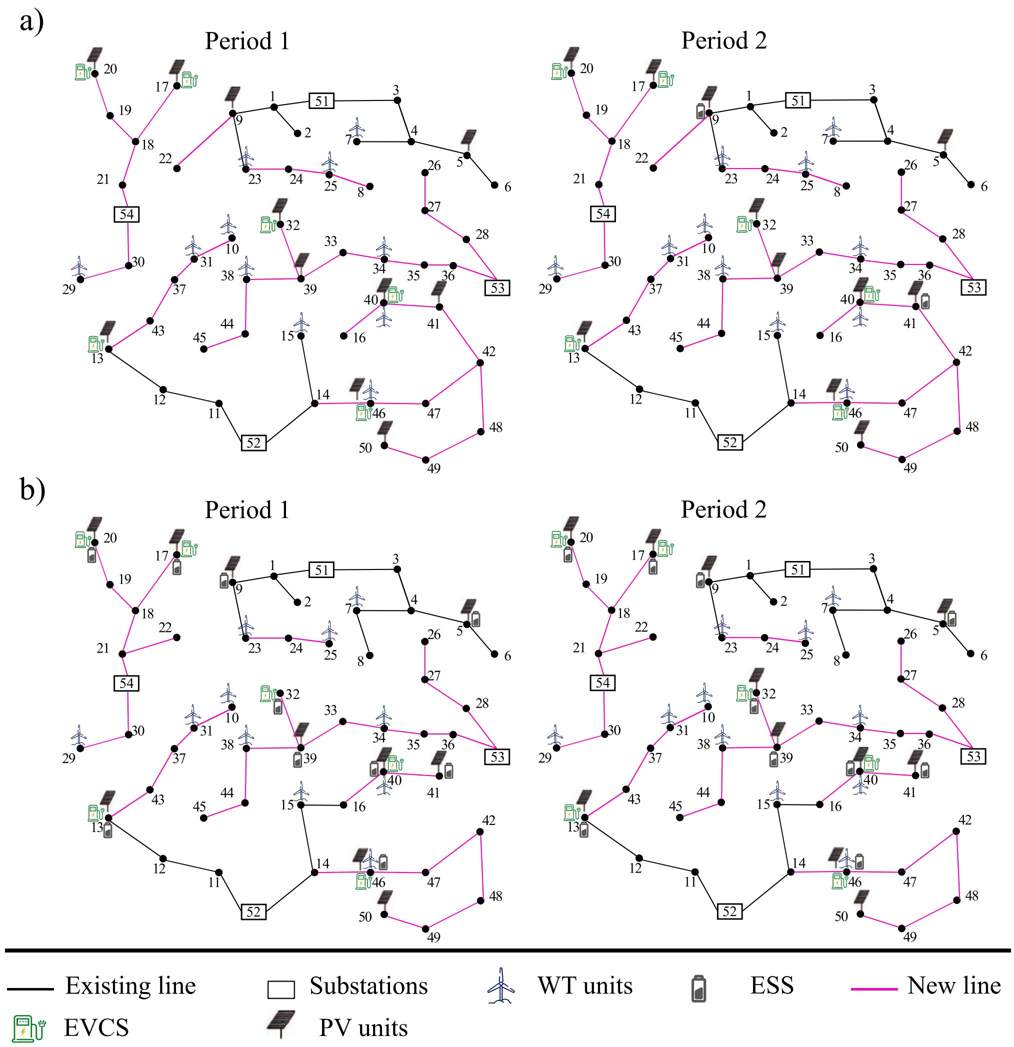

Fig. 8. Topology for the 54-node EDS planning: (a) Risk-neutral; (b) Risk-averse.

less in PV units due to the high impact of uncertainties in this technology (see Table VI).

The proposed expansion plans for the neutral and risk averse problems are illustrated in Fig. 8. The risk-neutral strategy installs only two ESSs at buses 9 and 41 in period 2. On the other hand, the risk-averse strategy installs ten ESSs at buses 5, 9, 13, 17, 20, 32, 39, 40, 41, and 46 in period 1 (see Fig. 8).

Finally, to validate and evaluate the quality of the solutions found by the proposed model, a comparison of the expected costs of the proposed model with a formulation closer to the original model (i.e., the mixed-integer second order cone programming (MISOCP) model) is presented in Table VII. Note that the linearization errors are negligible, demonstrating the high accuracy of the proposed model. Furthermore, an advantage of the proposed model compared to the MISOCP model is its lower computational cost (see Table VII). As the complexity of the problem increases, the MISOCP model has more difficulty achieving convergence than the MILP model. Finally, the original exact model (MINLP) does not converge to the problem presented here, demonstrating the importance of the model proposed in this work.

TABLE VII
LINEARIZATION ERRORS FOR THE 54-BUS EDS

Cases	**Risk-neutral**	**Risk-averse**
Total cost (proposed model)	321.45	327.63
Total cost (MISOCP model)	320.70	325.71
Linearization error (%)	0.23	0.59
Computational time (h) (proposed model)	13.89	8.10
Computational time (h) (MISOCP model)	175.29	126.35

The application of the proposed model to the 24 and 54-bus EDSs lead to similar conclusions. The main investment differences between the risk-neutral and risk-averse strategies in both systems are related to PV units and ESSs. Similar to the 24-bus EDS, the results for the 54-bus EDS indicate that the risk-averse compared to the risk-neutral strategy invests more in ESSs and less in PV units due to the high impact of uncertainties in this technology. The savings obtained by the risk-averse proposal if the worst scenario occurs increases in the 54-bus EDS, which obtained savings of \$20.92 million, while in the 24-bus EDS, the savings were approximately $19 million in total cost compared to the risk-neutral planning strategy. Finally, regarding computational times, the case studies (neutral and risk-averse approach) applied to the 54-bus EDS had a computational cost about three times higher than the cases applied to the 24-bus EDS (see Tables III and VII). These computational costs are reasonable in the context of the DSEP problem.

IV. Conclusion

A novel model for the multi-period planning of electrical distribution systems (EDS) and electric vehicles charging stations considering (EVCSs) CVaR has been presented to control the risk related to the planning decisions. In contrast to other proposals, the long-term uncertainties related to demand growth and carbon taxes according to the planning period have been addressed. The planning problem was optimized considering neutral and risk-averse strategies. Unlike previous approaches, the risk was evaluated from two perspectives: planning costs and carbon taxes.

The proposed model was also evaluated by optimizing only one risk at a time (carbon tax or planning cost). The risk-averse planning associated with the carbon tax obtained the best results related to the environmental perspective, investing more in PV units and presenting the lowest value of CO_2 emissions compared to the other case studies. However, this plan has an expected cost higher than the other cases. On the other hand, the proposal that includes only the CVaR related to the planning cost has the highest value of CO_2 emissions. However, such a proposal presented the best planning cost in the worst scenarios. The strategy addressing both risks offers an equilibrium between solutions prioritizing planning cost and carbon taxes. In addition, this strategy has the lowest expected cost compared to other risk-averse strategies.

The main advantage of the proposed model is to provide risk-based planning decisions considering economic and environmental aspects. In addition, the model presented is a flexible and easy-to-implement tool that can be adapted to different planning priorities. On the other hand, the proposed approach's main limitation is its high complexity, containing many binary and integer variables. Thus, the proposed model may present converge problems in some cases for large-scale systems.

In future research, a decentralized planning should be addressed, considering the priorities of different actors in the EDS, such as DER investors, EVCS investors, distribution system operators, among others. The proposed model can also be adapted by different agents considering their respective investments, promoting a collaboration strategy between DSO, EVCS investors, and DER owners using incentive policies. Furthermore, the model proposed here can be extended to a multi-objective proposal involving the risks related to CO_2 emissions and planning costs.

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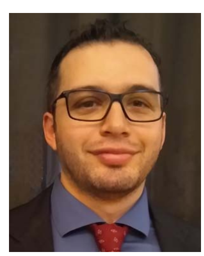

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