Robust Multi-Stage Substation Expansion Planning Considering Stochastic Demand

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***Abstract*—This paper presents a novel mixed-integer second-order cone programming model for the robust multi-stage substation expansion planning problem considering stochastic demand. The stochastic nature of the demands is considered through a robust model that uses chance constraints to guarantee that the substation capacity limits are satisfied within a given robustness probability. Furthermore, a multi-objective formulation that takes into account the total expected expansion planning cost and the robustness probability related to the violation of the substation capacity limits is proposed. The optimal solution of the proposed model is guaranteed by the convexity of the formulation, when classical optimization techniques are used in its solution. The results found (construction of new substations, reinforcement of existing substations, and service area of each substation) for two test systems demonstrate the efficiency and robustness of the proposed model. Additionally, Monte Carlo simulations were carried out in order to evaluate the extent to which the solutions found were able to satisfy the substation capacity limits.**

***Index Terms*—Mathematical programming, multi-stage substation expansion planning, robust optimization, stochastic optimization.**

NOMENCLATURE

The notation used throughout this paper is reproduced below for quick reference.

Sets:

C	Set of circuit types.
D	Set of load centers.
P	Set of stages.
S	Set of substations.
T	Set of substation types.
V	Set of load levels.

Functions:

f_1	Objective function related to the total expected expansion planning cost.
f_2	Objective function related to the violation of the substation capacity limits.

Constants:

α_p	Initial year of stage p.
$\pi_{s,v}$	Energy cost at substation s at load level v.
$\beta_{p,d}$	Binary parameter that defines if there is demand at load center d in stage p.
$\overline{\Delta V}$	Maximum voltage magnitude drop.
ϵ	Robustness parameter used for the capacity constraint of the substations.
κ_v	Factor used to calculate demand at load level v from nominal demand.
λ^c	Annual rate failure rate per kilometer of a circuit.
λ^s	Annual rate failure rate of a substation.
$\psi(\epsilon)$	Normalized Z-value for the percentile $1-\epsilon$.
ϕ	Power factor of the loads.
ρ	Penalization factor for energy not served.
$\sigma_{p,d,v}$	Standard deviation of the demand at load center d in stage p at load level v.
τ_c	Average repair time of a fault in a circuit.
τ_s	Average duration of failure in a substation.
τ_v	Number of hours in a year at load level v.
$\Theta^0_{s,t}$	Binary parameter that defines if there is a substation of type t at node s at the beginning of the horizon planning.
C^f_c	Construction cost of a circuit using type c.
$C^{\text{rep}}_{h,t}$	Cost related to the reinforcement of a substation from type h to t.
C^{SE}_t	Construction cost of a substation using type t.
γ_t	Loss factor of substation type t.
I	Investment interest rate.
$\overline{I}_c$	Maximum current magnitude for circuit type c.
$l_{s,d}$	Distance between substation at node s and load center d.
n_p	Number of years of stage p.
$S^d_{p,d,v}$	Mean value of the demand at load center d in stage p at load level v.
$\overline{S}_t$	Capacity of substation type t.

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V_{nom} Nominal voltage magnitude.

Z_c Impedance of circuit type c.

Variables:

$x_{p,s,d,c}$ Binary variable for the construction of a circuit between substation at node s and load center at node d, using circuit type c in stage p.

$y_{p,s,d,c}$ Binary variable for the operation of a circuit between substation at node s and load center at node d, using circuit type c in stage p.

$w^r_{p,s,h,t}$ Binary variable for the reinforcement of a substation at node s from type h to t in stage p.

$w_{p,s,t}$ Binary variable for the construction of substation type t at node s in stage p.

$z_{p,s,t}$ Binary variable for the operation of substation type t at node s in stage p.

FC Fixed cost.

VC Variable cost.

EENS Expected energy not supplied cost.

$S^g_{p,s,t,v}$ Expected generated power of the substation type t at node s in stage p at load level v.

$\tilde{S}^g_{p,s,t,v}$ Stochastic generated power of the substation type t at node s in stage p at load level v.

$r_{p,s,t}$ Auxiliary variable that represents the difference between the substation capacity and the generated power of substation type t at node s in stage p.

$q_{p,s}$ Auxiliary variable used in the chance substation capacity constraint of substation at node s in stage p.

I. Introduction

THE electrical distribution system expansion planning problem consists of determining the optimal expansion plan for the equipment of the distribution system in order to supply the future load, while satisfying operational conditions. In this context, the data related to the distribution system is usually represented by the system data at the base year, the load data for the planning horizon, the geographical points at which new substations can be built or existing substations can be reinforced, the existing feeders and the paths to build new feeders, the types of circuits that can be built, and in detailed cases, the types of shunt capacitors and voltage regulators that can be installed in the system [1].

The possibility of installing several types of device with very diverse characteristics makes the electrical distribution system expansion planning problem highly complex and difficult to solve. This kind of problem is hard to solve because the planning decisions related to the substations are represented by binary variables, and each feeder type is represented using binary variables. This forms a mathematical model of a combinatorial nature, which is known as an NP-hard problem. To date, there have been two kinds of approaches to electrical energy distribution system planning: 1) planning that prioritizes the allocation of substations in the distribution system and represents the rest of the problem in an approximate form (this type of approach is known in the specialized literature as the siting, sizing, and timing of distribution substations), and 2) planning that considers the siting of substations and other expansion alternatives simultaneously. The reasons for approaching the problem by allocating substations in the first phase and considering other alternatives in the second phase are the following: 1) the distribution system expansion planning problem is too complex to be treated in an integrated manner in practical applications; 2) the costs corresponding to the allocation of substations are too high compared to the costs related to other expansion alternatives, such as the cost of feeders, capacitor banks, and voltage regulators; and 3) there are conflicting opinions as to whether the allocation of substations should be considered along with transmission system expansion, treated independently, or integrated with other distribution system expansion alternatives [2].

There are two types of electrical distribution system (EDS) expansion planning: static and multi-stage (or dynamic). In static planning, the planning is aimed at accommodating the projected demand at the end of the planning period. Multi-stage planning defines not only the ideal location, investment type, and capacity of the investments, but also the most appropriate time to make such investments. In this way, the continuous growth of the demand is always absorbed by the EDS in an optimal way. Due to the coupling between the various stages, it is much more difficult to formulate and solve the multi-stage planning problem. An approximated method (pseudo-dynamic approach) for multi-stage planning is to solve a sequence of static planning problems; the solution of the static planning in one stage will comprise the base data for the solution of the static planning in the next stage.

This work addresses the optimal expansion planning of substations, i.e., the siting, sizing, and timing of distribution substations, and, as such, the rest of the distribution system is represented approximately. However, the proposed method also considers multi-stage planning and the stochastic modeling of demand. In this problem, the data are represented by the future demands in each geographical zone and the points at which substations can be allocated. Additionally, it is assumed that the distances between each load center and substation candidate point are known. Furthermore, the characteristics of the circuit types are given, and the connections between load centers and substations are considered to be direct. Therefore, the solution will naturally be radial.

In the specialized literature, there are many works that address the problem of the substation expansion planning (SEP) problem in distribution systems. In [3], the SEP problem is solved using a branch-exchange algorithm, which has been used to solve several optimization problems in distribution systems. Branch-exchange can occur when two close substations exchange two load points, or when a load is transferred from one substation to the other. In this process, once a set of substations is chosen, a feasible solution must be found by connecting each load center to the nearest substation.

In [4], a heuristic combination optimization algorithm is used to solve the SEP problem. However, the most important aspect of this approach is that there are no points predetermined for the allocation of the substations. Rather, any position that acts as a load center is also a candidate for substation allocation. This type of approach increases the complexity of the formulation.

The method presented in [5] applies a traditional genetic algorithm to solve the SEP problem. In this case, the authors use two crossover and four different mutation operators. Additionally, the objective function takes a complex form in which the costs related to the connection of the high voltage transmission system are considered.

A very interesting mathematical model for the SEP problem is proposed in [6]. The authors present a mixed integer linear programming model for the multi-stage SEP problem in which the linear formulation is developed using efficient transformations over a nonlinear formulation. Therefore, the fundamental contribution of this work is the formulation of the linear model. The authors solve the mixed integer linear programming model using a commercial solver.

A mixed integer nonlinear programming model for the multi-stage SEP is developed in [7]. In this work, the authors use a commercial solver to solve the nonlinear mathematical model for the small-scale system presented in [6]. Furthermore, it must be noted that the mathematical model corresponds to the static planning problem, and so the authors apply a pseudo-dynamic strategy to solve the multi-stage planning problem. The authors of [7] discuss the differences between the planning problems considering the allocation of substations or construction of feeders (subsystem techniques) and the strategies for the jointly planning substations and feeders (total system techniques).

A genetic algorithm to solve the multi-stage SEP is presented in [8]. The authors distinguish between short-term and long-term planning, identifying the optimal location and sizing of substations as a long-term planning problem. The uncertainties of the loads are taken into account using a fuzzy logic-based model. The authors use a genetic algorithm to solve the problem according to a pseudo-dynamic strategy.

A detailed mathematical formulation for the optimal multi-stage allocation of substations is presented in [9] and includes distribution generation as an alternative to the expansion of the distribution system. The resulting model is a mixed integer nonlinear programming formulation that can be solved using a commercial solver. In [10], the same authors of the aforementioned work present a mathematical formulation that is then transformed into a mixed integer linear programming model. Other important theoretical and practical contributions to the optimal allocation of substations can be found in [11]–[13]. A hybrid heuristic and learning automata-based algorithm for expansion planning of substations was presented in [14]. Finally, this kind of approach has been used in recent publications such as [15]–[17] to solve the problem with specialized evolutionary algorithms. References [15] and [16] use an imperialist competitive algorithm for the optimal sizing, siting, and timing of substations in static and multi-stage planning. In [17], an enhanced evolutionary algorithm is used to solve the expansion planning for large-size distribution systems.

As previously mentioned, there is another way to carry out the expansion planning of the substations in distribution systems, which integrates the location of the substations and the selection of the feeders. In [18] and [19], mixed integer linear programming formulations for the multi-stage planning are presented and solved using commercial solvers. In [20], a strategy is used to separate the problem into feeder areas, employing a genetic algorithm to allocate the feeders. A constructive heuristic algorithm is proposed in [21] to solve the integrated planning of distribution systems, while in [22], a mixed integer linear programming formulation for the multi-stage planning of distribution systems considering reliability is developed. In [23], a direct solution technique to solve the distribution system expansion planning is proposed.

In order to plan the expansion of the distribution system, future demand must be estimated. Usually, demand values are considered as deterministic values [4]–[7]. However, the stochastic behavior of future loads can lead to unfeasible expansion plans if the actual loads surpass the estimated values. Therefore, it is important to model the stochastic nature of the demand.

A novel mixed-integer second-order conic programming model for the robust multi-stage substation expansion planning problem considering stochastic demand is proposed in this paper. The expansion alternatives are the construction of new substations and the reinforcement of existing substations. Additionally, the proposed formulation determines the service area of the substations, selecting an appropriate circuit type with which to connect each load center to its corresponding substation. The multi-stage representation allows the distribution system operator to divide the investments in the substations into several stages along a planning horizon, which can lead to better solutions than with static planning. Additionally, the robust formulation considers the effect of stochastic loads on the capacity limits of the substations. Chance constraints are developed in order to guarantee that the substation capacity limit is satisfied within a given robustness probability. The optimal solution of the model is found using commercial MILP solvers that guarantee the optimal solution for second-order cone programming models. Results found for two tests systems demonstrate the efficiency and the robustness of the proposed mathematical formulation. Furthermore, Monte Carlo simulations were carried out in order to evaluate the performance of the solutions found with respect to the satisfaction of the substation capacity limits.

The main contributions of this paper are:

- a novel mixed-integer second-order cone programming model for the robust multi-stage substation expansion planning problem, which guarantees the optimal solution of the problem and can be solved efficiently using commercial solvers;
- a robust formulation for the substation expansion planning problem that considers stochastic demands;
- a multi-objective representation of the substation expansion planning problem in which the total expansion planning cost and the robustness probability are conflicting objectives.

The remainder of this paper is organized as follows. The substation expansion planning problem and the proposed mixed-integer second order conic programming model for its solution are presented in Section II. Section III presents the Tests and Results, while Section IV outlines the main conclusions.

II. Substation Expansion Planning Problem in Electrical Distribution Systems

The optimal substation expansion planning problem determines the construction of new substations and the reinforcement of existing substations in order to meet growth in demand. The solution for the SEP problem defines the service area of the substations, making it possible to determine the optimal paths to satisfy demand and to consider operational constraints, such as the capacities of substations, voltage limits, and the maximum currents in feeders.

In this work, the SEP problem is modeled as a multi-stage investment decision, determining the most appropriate time to execute each investment. The following assumptions are made in order to formulate a mathematical model for the SEP problem:

- The loads are distributed geographically and concentrated at points called load centers.
- The load centers are connected directly to the substations.
- The loads are represented by their apparent power.
- The substations can be built/reinforced using a set of substation types. The construction/reinforcement costs are known and take into account the cost of connecting the substation to the subtransmission system, as well as maintenance and operation costs.
- A set of circuit types is available to construct circuits that connect the load centers to the substations. The construction cost for each type includes the maintenance of the circuit.
- The demands at the load centers are stochastic parameters that follow a normal probability distribution.
- The expansion plan must satisfy the capacity limits of the substations, the voltage limits, and the current capacities of the feeders.
- The variation of the demands is represented through load levels.
- The planning horizon is divided into different stages at which the expansion planning decisions can be executed.

As discussed in [6], in order to get a set of suitable candidate locations for new substations, besides electrical considerations, the selection need to takes into account the expansion plan of the city, as well as environmental constraints. Based on this information, "all possible site locations are investigated and classified into unsuitable, candidate, and future evaluation sites" by the distribution system planner [6].

A. Mixed-Integer Second Order Conic Programming Model for the Robust Multi-Stage Substation Expansion Planning Problem Considering Stochastic Demand

The robust multi-stage substation expansion planning problem can be modeled as a mixed-integer second-order cone programming model using (1)–(19). The second-order cone programming (SOCP) problem is a type of non-linear convex optimization problem wherein the objective is a convex function and the constraints define a convex set. SOCP is useful in a wide variety of application areas, including engineering and financial management. Several efficient methods for SOCP have been developed in the last few years. The SOCP problem can be used to represent several common convex programming problems. In effect, linear programming problems, convex problems containing hyperbolic, quadratic norm constraints, and many other nonlinear convex optimization problems can be reformulated as SOCPs [24].

The objective function (1) minimizes the total expected expansion planning cost, which consists of three parts: 1) the fixed cost (FC) corresponding to reinforce the existing substations, to construct new substations, and constructing circuits that connect the substations to the demand centers; 2) the variable costs (VC) related to the expected energy costs and power losses at the substations (calculated using the mean values for the demands, considering load levels and the factor μ_p to calculate the operation cost over the planning horizon); and 3) the expected energy not supplied cost (EENS) related to the penalization cost of the energy not supplied due to failure of substations and circuits. All of the terms of the objective function are multiplied by the factor $(1+I)^{-\alpha_p}$ in order to calculate the present value of the total expected expansion planning cost. Factor μ_p is calculated as $[1-(1+I)^{-n_p}]/I$. The objective function defined by (1) was based on the proposals presented in [5], [10].

Constraint (2)–(9) are logical conditions between the investment and the operational variables. Constraint (2) is a logical condition establishing that a substation can be reinforced from substation type h to t if that substation has already been constructed or reinforced as type h. Similarly, (3) guarantees that a substation of type t can be in operation if that substation has already been constructed or reinforced as type t. A circuit can be in operation if it has already been constructed according to its corresponding circuit type, as shown in (4). Additionally, a circuit must be in operation if its demand center is active (5), fact identified by parameter $\beta_{p,d}$.

Specifically, (6)–(9) limit the selection of an investment or operation variable for just one type for substations and circuits. Constraints (6) and (7) establish that, for a given stage, a substation can only be constructed/reinforced and operated using a certain substation type. In the same way, (8) and (9) guarantee that, for a given stage, a circuit connecting a substation and a load center can only be constructed and operated using a certain circuit type.

The expected power generated by a substation is limited by (10), according to the maximum capacity of each substation type and the corresponding operation variable. That generated power is calculated for each load level considering power losses in the circuits, as shown in (11). Constraint (12) is a chance constraint for the generated power at the maximum load level (assumed as $v=1$). Considering the stochastic behavior of the loads, this chance constraint guarantees that the probability of satisfying the capacity of a substation is above a defined probability (robustness probability related to the robustness parameter ϵ).

The maximum voltage magnitude drop and the current magnitude limits in the circuits are represented by (13) and (14), respectively; both equations include the power losses in the circuits. The binary nature of the decision variables is represented by (15)–(19):

$$
\begin{aligned}
&\min \mathrm{FC} + \mathrm{VC} + \mathrm{ENSC}\\
&\mathrm{FC} = \sum_{p\in P}\sum_{s\in S}\left(\sum_{h\in T}\sum_{t\in T} C^{\mathrm{rep}}_{h,t} w^r_{p,s,h,t} + \sum_{t\in T} C^{SE}_t w_{p,s,t}\right.\\
&\qquad \left. + \sum_{d\in D}\sum_{c\in C} C^f_c l_{s,d} x_{p,s,d,c}\right)(1+I)^{-\alpha_p}\\
&\mathrm{VC} = \sum_{p\in P}\sum_{s\in S}\sum_{t\in T}\sum_{v\in V}\left(\tau_v \pi_{s,v}\phi S^g_{p,s,t,v}\right.\\
&\qquad \left. + \tau_v \gamma_t {S^g_{p,s,t,v}}^2 \mu_p\right)(1+I)^{-\alpha_p}\\
&\mathrm{EENS} = \sum_{p\in P}\sum_{s\in S}\sum_{d\in D}\sum_{c\in C}\sum_{v\in V} \rho \frac{\tau_v}{8760}\phi S^d_{d,p} y_{p,s,d,c}\\
&\qquad \times (\tau_s\lambda_s + \tau_c\lambda_c l_{s,d})\mu_p (1+I)^{-\alpha_p}
\end{aligned}
\tag{1}
$$

Subject to:

$$w^r_{p,s,h,t} \leq \Theta^0_{s,h} + \sum_{\substack{u\in P\\u<p}} w_{u,s,h} + \sum_{\substack{u\in P\\u<p}}\sum_{q\in T} w^r_{u,s,q,h} \quad \forall p\in P, s\in S, h\in T, t\in T \tag{2}$$

$$z_{p,s,t} \leq \Theta^0_{s,t} + \sum_{\substack{u\in P\\u\leq p}} w_{u,s,t} + \sum_{\substack{u\in P\\u\leq p}}\sum_{h\in T} w^r_{u,s,h,t} \quad \forall p\in P, s\in S, t\in T \tag{3}$$

$$y_{p,s,d,c} \leq \sum_{\substack{u\in P\\u\leq p}} x_{u,s,d,c} \quad \forall p\in P, s\in S, d\in D, c\in C \tag{4}$$

$$\sum_{s\in S}\sum_{c\in C} y_{p,s,d,c} = \beta_{p,d} \quad \forall p\in P, d\in D \tag{5}$$

$$\sum_{t\in T} w_{p,s,t} + \sum_{h\in T}\sum_{\substack{t\in T\\t>h}} w^r_{p,s,h,t} \leq 1 \quad \forall p\in P, s\in S \tag{6}$$

$$\sum_{t\in T} z_{p,s,t} \leq 1 \quad \forall p\in P, s\in S \tag{7}$$

$$\sum_{c\in C} x_{p,s,d,c} \leq 1 \quad \forall p\in P, s\in S, d\in D \tag{8}$$

$$\sum_{c\in C} y_{p,s,d,c} \leq 1 \quad \forall p\in P, s\in S, d\in D \tag{9}$$

$$0 \leq S^g_{p,s,t,v} \leq \overline{S}_t z_{p,s,t} \quad \forall p\in P, s\in S, t\in T, v\in V \tag{10}$$

$$\sum_{t\in\Omega_T} S^g_{p,s,t,v} = \sum_{d\in D}\sum_{c\in C}\left(S^d_{p,d,v} + \left(\frac{S^d_{p,d,v}}{V_{\text{nom}}}\right)^2 Z_c l_{s,d}\right) y_{p,s,d,c} \quad \forall p\in P, s\in S, v\in V \tag{11}$$

$$\text{Prob}\left\{\sum_{t\in\Omega_T} \tilde{S}^g_{p,s,t,1} \leq \sum_{t\in T}\overline{S}_t z_{p,s,t}\right\} \geq 1-\epsilon \quad \forall p\in P, s\in S \tag{12}$$

$$\sum_{s\in S}\sum_{c\in C}\left(S^d_{p,d,v} + \left(\frac{S^d_{p,d,v}}{V_{\text{nom}}}\right)^2 Z_c l_{s,d}\right) Z_c l_{s,d} y_{p,s,d,c} \leq V_{\text{nom}}\overline{\Delta V}, \forall p\in P, d\in D \tag{13}$$

$$\left(S^d_{p,d,v} + \left(\frac{S^d_{p,d,v}}{V_{\text{nom}}}\right)^2 Z_c l_{s,d}\right)/V_{\text{nom}} \leq \sum_{s\in S}\overline{I}_c y_{p,s,d,c} \quad \forall p\in P, d\in D, c\in C \tag{14}$$

$$w_{p,s,t} \in \{0,1\} \quad \forall p\in P, s\in S, t\in T \tag{15}$$

$$w^r_{p,s,h,t} \in \{0,1\} \quad \forall p\in P, s\in S, h\in T, t\in T \tag{16}$$

$$x_{p,s,d,c} \in \{0,1\} \quad \forall p\in P, s\in S, d\in D, c\in C \tag{17}$$

$$z_{p,s,t} \in \{0,1\} \quad \forall p\in P, s\in S, t\in T \tag{18}$$

$$y_{p,s,d,c} \in \{0,1\} \quad \forall p\in P, s\in S, d\in D, c\in C. \tag{19}$$

Chance constraint (12) can be represented by (20), as shown in Appendix A. This constraint takes into account the expected power generated, the variation of demand at the load centers, and the power limits of the substation in operation. As described in the Appendix, the function $\psi(\epsilon)$ represents the normalized Z-value corresponding to the area under the normal distribution curve for the percentile $1-\epsilon$:

$$\sum_{t\in\Omega_T} S^g_{p,s,t,1} + \psi(\epsilon)\sqrt{\sum_{d\in D}\sum_{c\in C}\sigma^2_{p,d,1} y^2_{p,s,d,c}} \leq \sum_{t\in T}\overline{S}_t z_{p,s,t} \quad \forall p\in P, s\in S. \tag{20}$$

In order to specifically obtain a mixed-integer second-order cone programming model for the robust multi-stage substation expansion planning problem, (20) is substituted by (21)–(25). Constraint (23) is a second-order cone constraint that establishes a relationship between the capacity of a substation, and the mean and the variation of the demand on that substation:

$$r_{p,s,t} = \overline{S}_t z_{p,s,t} - S^g_{p,s,t,1} \quad \forall p\in P, s\in S, t\in T \tag{21}$$

$$q_{p,s} = \sum_{t\in T} r_{p,s,t} \quad \forall p\in P, s\in S, t\in T \tag{22}$$

$$\psi(\epsilon)\sum_{d\in D}\sum_{c\in C}\sigma^2_{p,d,1} y^2_{p,s,d,c} \leq q^2_{p,s} \quad \forall p\in P, s\in S \tag{23}$$

$$r_{p,s,t} \geq 0 \quad \forall p\in P, s\in S, t\in T \tag{24}$$

$$z_{p,s,t} \geq 0 \forall p\in P, s\in S. \tag{25}$$

Thus, the mixed-integer second-order cone programming model for the robust multi-stage substation expansion planning problem is defined by (1)–(11), (13)–(19), and (21)–(25). By including (21)–(25), the proposed model is a robust formulation for the optimal expansion of substations considering the stochastic nature of the loads. This optimization model can be solved using classical optimization techniques that guarantee the optimal solution for this convex problem.

B. *Multi-Objective Formulation for the Substation Expansion Planning Problem*

The model presented above minimizes the costs related to substation expansion planning, while satisfying the substation capacity limits within a given probability, as defined by the robustness parameter ϵ. Within this context, a multi-objective formulation for the substation expansion planning problem can be defined by considering two different and conflicting objectives: the total expected expansion planning cost (f_1) and the robustness probability related to the violation of the substation capacity limits (f_2). In effect, if the distribution system operator wants to improve the robustness of the expansion plan (reduce the value of f_2), the investment cost will increase.

The multi-objective formulation can be written as show in (26)–(28):

$$\min\{f_1, f_2\} \tag{26}$$

$$f_1 : (1) \tag{27}$$

$$f_2 : \text{maximum}\left\{1 - \text{Prob}\left\{\sum_{t\in\Omega_T}\tilde{S}^g_{p,s,t,1} \leq \sum_{t\in T}\overline{S}_t z_{p,s,t}\right\}, p\in P, s\in S\right\}. \tag{28}$$

This mathematical formulation for the multi-objective substation expansion planning problem can be solved by increasing the value of the robustness parameter ϵ in order to generate solutions that satisfy the substation capacity constraints with greater probability. Therefore, the Pareto front for this multi-objective formulation can be generated by successively solving the mixed-integer second-order cone programming model and setting the robustness parameter ϵ as described in the following procedure:

1) Let $\epsilon = 50\%$, which implies $\psi(\epsilon) = 0$ (i.e., consider deterministic loads by using their mean values). Let it $= 1$.

TABLE I
SUBSTATION TYPES

t	C_t^{SE} (10^3\$)	$\overline{S}_t$ (MVA)	γ_t (\$/MVA^2h)
t_1	1000	10	0.050
t_2	1800	20	0.045
t_3	2500	30	0.040

TABLE II
CIRCUIT TYPES

c	C_c^f (10^3\$/km)	$\overline{I}_c$ (A)	Z_c (Ω/km)
c_1	30	200	0.5
c_2	50	400	0.3

2) Solve the robust multi-stage substation expansion planning problem as defined by (1)–(11), (13)–(19), and (21)–(25) to obtain the itth Pareto front solution. If the problem is feasible, go to step 3. Otherwise exit.
3) Evaluate the solution obtained using Monte Carlo simulations, and calculate objective function f_2.
4) Let $\text{it} = \text{it} + 1$, set $\epsilon = f_2 - 0.1\%$, and return to step 2.

The Monte Carlo simulation mentioned in Step 3 of the above procedure uses the solution obtained in Step 2 and generates load profiles considering the probability parameters of the loads (mean value and standard deviation). The operation of the system is evaluated for each load profile in order to establish if there has been a violation of the substation capacities. After a determined number of iterations, the probability of satisfaction of the substation capacities is calculated (f_2). In this work, the Monte Carlo simulation was executed in Matlab with 100 000 iterations.

III. TESTS AND RESULTS

The proposed model was implemented in AMPL [26] and solved with CPLEX [27] using a computer with an Intel i7 4770 processor. Two test systems were used: 1) First case: test system with 4 substation nodes and 10 load centers; and 2) Second case: test system with 9 substation loads and 65 load centers, which was based on the system presented in [10].

A. First Case

The proposed model was tested using a distribution system with 4 substation nodes and 10 load centers. For this test system, there were three substation types and two circuit types, as shown in Tables I and II. It cost $\$800 \cdot 10^3$ to reinforce substation type 1 to type 2, $\$1600 \cdot 10^3$ to reinforce substation type 1 to type 3, and $\$800 \cdot 10^3$ to reinforce substation type 2 to type 3. At the beginning of the planning horizon, there was a substation of type t_1 at node s_2.

The nominal voltage magnitude of the system was 15 kV, while the maximum voltage magnitude drop was 10%. The investment interest rate was 10%. In addition, it was assumed that the power factor of the loads was 0.90. Parameter λ^s was 0.5 failures/year, τ_s was 5 h, λ^c was 0.1 failures/year/km, τ_c was 3 h, and ρ was \$5000/MWh. Three planning stages were considered, each with a duration of 5 years. The parameters related to the conductor types are shown in Table II.

There were three load levels, and the parameters related to the load levels are presented in Table III. The nominal loads are presented in Table IV. It was assumed that the loads followed a normal distribution with means equal to the nominal values, and standard deviations equal to 15% of the nominal values.

TABLE III
LOAD LEVEL PARAMETERS

v	$\pi_{s,v}$ (\$/MVWh)	τ_v (h)	κ_v
v_1	100	1000	1.0
v_2	80	6760	0.5
v_3	50	1000	0.4

TABLE IV
NOMINAL LOADS (MVA)

p	Load center									
	1	2	3	4	5	6	7	8	9	10
p_1	2	0	6	4	4	0	0	2	0	4
p_2	3	3	7	6	5	0	4	4	5	5
p_3	4	4	8	7	6	6	6	5	6	6

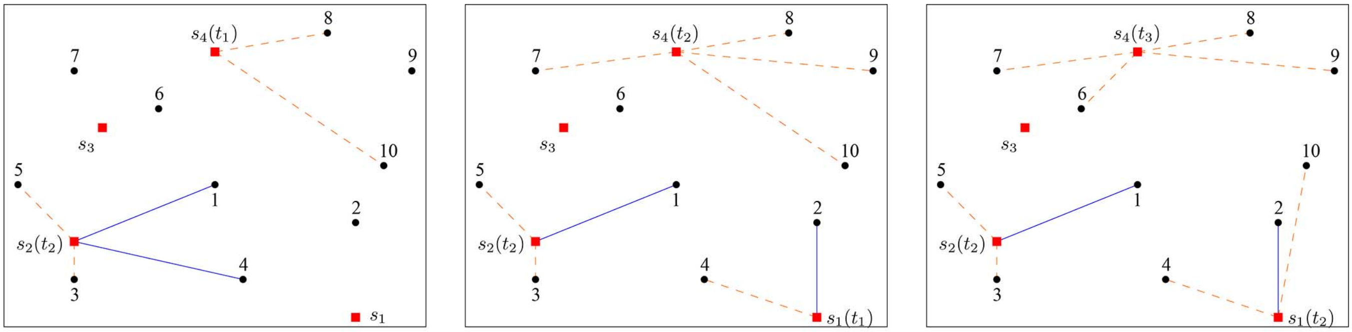
TABLE V
SUMMARY OF THE RESULTS FOR THE FIRST CASE

Test	Base SEP (\$M)	Robust SEP 10% (\$M)	Robust SEP 5% (\$M)
Total cost	103.678	103.790	104.095
Substation investment cost	3.535	3.723	4.031
Substation construction cost	1.621	1.621	1.621
Substation reinforcement cost	1.914	2.102	2.410
Investment cost on feeders	2.110	1.954	1.954
Energy not served cost	1.890	1.903	1.903
Expected energy cost	95.820	95.879	95.878
Substation power losses cost	0.156	0.160	0.159
Time (s)	5	118	21

Three tests were carried out. The first test found the solution for the multi-stage SEP problem considering deterministic demands (Base SEP), represented by (1)–(11), and (13)–(19), i.e., (21)–(25) were disregarded. The second test found the solution for the robust multi-stage SEP problem (Robust SEP 10%) considering stochastic demands, as presented in Section II-A. For the second case, the robustness parameter used for the capacity constraint of the substations was 10%, so the factor $\psi(\epsilon)$ was 1.282. This robustness parameter ensured that the substation capacity constraint was satisfied with a probability of at least 90%. The third test found the solution for the robust multi-stage SEP problem (Robust SEP 5%) considering a robustness parameter ϵ equal to 5% (the factor $\psi(\epsilon)$ was 1.645). A summary of the tests is presented in Table V. The solutions found for each test are shown in Figs. 1–3.

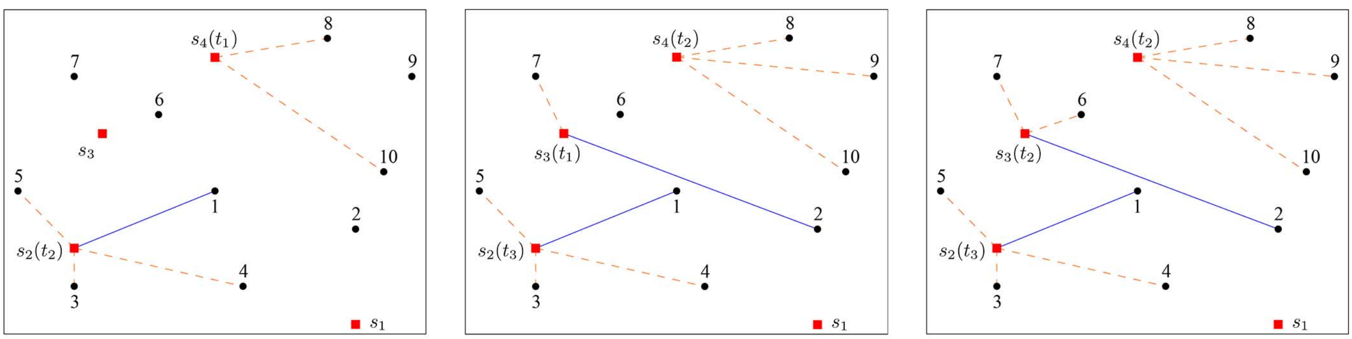
The substation investment cost for the Base SEP solution was \$3.535 million, while for the Robust SEP 10% solution it was \$3.723 million (about 5% higher). The substation investment cost for the Robust SEP 5% solution was \$4.031 million, about 14% higher than the corresponding value for the Base SEP solution. The additional investments carried out in the robust solutions guarantee that the capacities of the substations will be sufficient to meet the demand requirements within the constraints defined by the robustness factor.

In the Base SEP solution, substations were built at nodes 1, 2, and 4. Substation s_2 was reinforced in Stage 1, while s_4 was reinforced in Stages 2 and 3. There was no need to construct



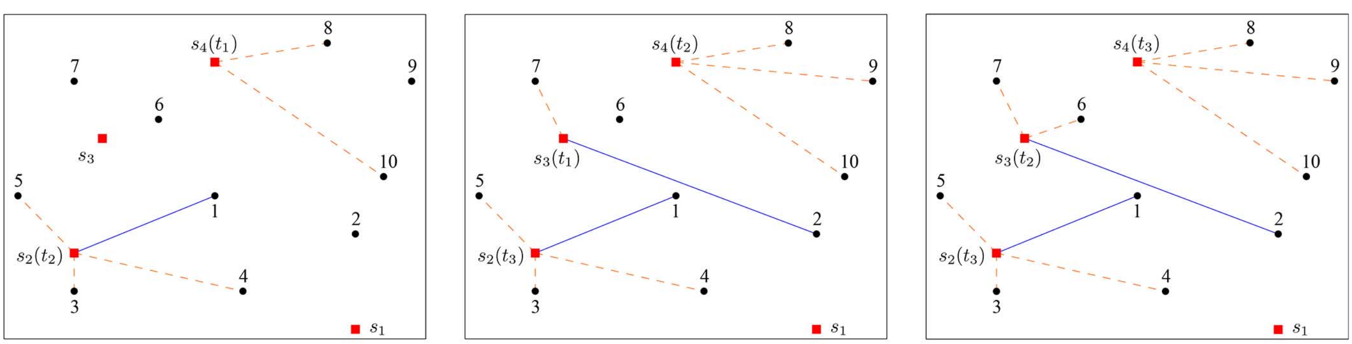
(a) (b) (c)

Fig. 1. Substation expansion planning for the first test system considering deterministic loads (circuits in continuous lines use c_1, in dashed lines use c_2). (a) Stage 1. (b) Stage 2. (c) Stage 3.



(a) (b) (c)

Fig. 2. Robust substation expansion planning for the first test system—Robust SEP 10% case (circuits in continuous lines use c_1, in dashed lines use c_2). (a) Stage 1. (b) Stage 2. (c) Stage 3.



(a) (b) (c)

Fig. 3. Robust substation expansion planning for the first test system—Robust SEP 5% case (circuits in continuous lines use c_1, in dashed lines use c_2). (a) Stage 1. (b) Stage 2. (c) Stage 3.

substation s_1 before Stage 2, but that substation was then reinforced in Stage 3. Note that load centers without demand in a given stage were not connected, i.e., they were only connected when needed in order to reduce investment costs.

In the Robust SEP 10% solution, three substations were constructed: s_2 and s_4 in the first stage and s_3 in the second stage. These substations were also reinforced. The main differences between this solution and the Base SEP solution were that substation s_3 was constructed instead of substation s_1, and for Stage 2, the sum of the substation capacities was 60 MVA, rather than 50 MVA, in order to satisfy the capacity limits of the substations considering stochastic demands.

The Robust SEP 5% solution was similar to the Robust SEP 10% solution. The only difference was that in the Robust SEP 5% solution, substation s_4 was reinforced at Stage 3 (achieving a substation capacity of 80 MVA rather than 70 MVA) in order to guarantee that the capacity constraint of this substation is satisfied with greater probability.

In order to evaluate the robustness of the substation capacity constraints of the solutions, Monte Carlo simulations were carried out considering the normal distribution of the stochastic loads. Table VI shows the percentage of iterations in which the capacity constraints of a substations were violated. The fault percentages obtained through the Monte Carlo simulations indicated that the Base SEP had the worst performance, but the lowest cost. The robust solutions, however, limited the fault percentage according to the related robustness parameter, but had increased investment costs. Note that the solution for the Robust

TABLE VI
FAULT PERCENTAGES OF THE SUBSTATION CAPACITY CONSTRAINTS OBTAINED WITH MONTE CARLO SIMULATIONS FOR THE FIRST CASE

	p_1				p_2				p_3			
	s_1	s_2	s_3	s_4	s_1	s_2	s_3	s_4	s_1	s_2	s_3	s_4
Base SEP	0.00	0.26	0.00	0.00	24.81	0.03	0.00	17.22	7.75	18.49	0.00	0.02
Robust SEP 10%	0.00	0.21	0.00	0.00	0.00	0.00	0.01	0.00	0.00	1.81	0.82	7.61
Robust SEP 5%	0.00	0.21	0.00	0.00	0.00	0.00	0.01	0.00	0.00	1.81	0.82	0.00

TABLE VII
SOLUTIONS FOUND USING THE PROPOSED MULTI-OBJECTIVE FORMULATION FOR THE FIRST CASE

Robustness parameter ϵ	Total expected cost f_1 (10^6\$)	Robustness probability f_2 (%)	Time (s)
50.0%	103.678	24.8	5
24.7%	103.696	23.6	57
23.5%	103.721	17.9	9
17.8%	103.774	17.2	12
17.1%	103.790	7.6	118
7.5%	103.819	7.1	6
7.0%	104.007	5.1	23
5.0%	104.095	1.8	21
1.7%	104.144	1.6	12
1.5%	104.188	0.8	32
0.7%	104.192	0.2	17
0.1%	104.449	< 0.1	55

SEP 10% case only had a fault percentage larger than 5% in substation s_4 in the third stage. The Robust SEP 5% case proposed a reinforcement for this substation, which led to an improvement in the corresponding fault percentage.

Using the multi-objective formulation for the substation expansion planning problem, the non-dominated solutions of the Pareto front were generated, while controlling the robustness parameter ϵ using the procedure presented in Section II-B. The total expected expansion costs and robustness parameters related to several solutions are shown in Table VII. The results obtained indicate that the proposed method can provide a set of non-dominated solutions for the substation expansion planning problem, which allows the distribution system operator to select a suitable proposal that considers expansion cost, as well as the robustness of the solution.

The Pareto front for the multi-objective substation expansion planning problem is shown in Fig. 4 (the solutions were connected with dashed lines to facilitate the visualization of the front). This figure illustrates that the objectives defined by f_1 and f_2 (i.e., the total expected expansion planning cost and the robustness of the expansion plan) are in conflict, since improving the robustness of the expansion plan requires a corresponding increase in investment. Based on the Pareto front, the distribution system planner can select the more suitable solution according to the design criteria of the electrical utility. So, if the electrical utility wants to increase the robustness of the substation expansion plan, the Pareto front makes it possible to determine the increase in investment cost in order to obtain the required level of robustness.

B. Second Case

The second test system has 9 substation nodes and 65 load centers, and the planning is made up of 6 stages over 1 year.

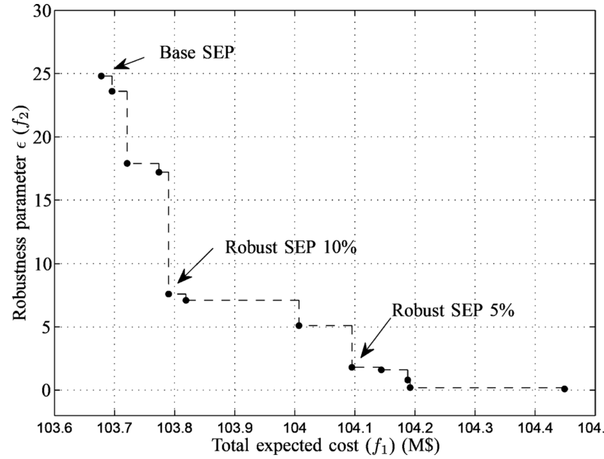


Fig. 4. Pareto front found using the proposed multi-objective formulation for the first case.

TABLE VIII
SERVICE AREA OF SUBSTATIONS OF THE LOWEST COST SOLUTION FOR THE SECOND CASE

Substation	Service Area (Load centers connected)
1	26, 28, 32, 33, 40, 41, 46, 49, 52, 53, 54, 56, 57, 58, 59, 60
2	30, 34, 35, 37, 42, 45, 48, 50, 61
3	17, 19, 20, 22, 23
4	31, 38, 39, 47, 51
5	14, 16, 18, 55, 65
6	4, 6, 7, 8, 9, 43, 44, 62, 64
7	29, 36
8	1, 2, 3, 5, 10, 11, 12, 13, 15, 27
9	21, 24, 25, 63

This test system is based on the case presented in [10]. The substations at nodes 1 to 5 are existing substations (with capacities of 90, 60, 30, 30, and 30 MVA, respectively), while nodes 6 to 9 are candidate substations. Unlike the case in [10], the energy cost $\pi_{s,v}$ for the base load level is the same for all substations (30 \$/MWh).

For this case, the solution with the lowest cost found by the proposed method built 4 candidate substations. The service areas for each substation are shown in Table VIII. This solution had a cost of \$249.561 million, and the cost of substations and feeders were \$3.337 million and \$3.585 million, respectively.

On the other hand, the solution where f_2 equals 2.6% had a cost of \$250.562 million. The investments in substations and feeders for this solution were \$4.589 million and \$3.423 million, respectively, which corresponds to a 15.7% increase in the investment cost. The main difference in this solution, compared to the lowest cost solution, is that substations at nodes 6 and 7 were constructed with larger capacities in order to achieve a more robust configuration of the substations.

The multi-objective formulation was applied for this case in order to get a set of non-dominated solutions. The Pareto front obtained for the multi-objective substation expansion planning problem for the second case is shown in Fig. 5 and the total expected expansion costs and robustness parameters related to the solutions are shown in Table IX. The capacity of each substation for the second case is shown in Table X.

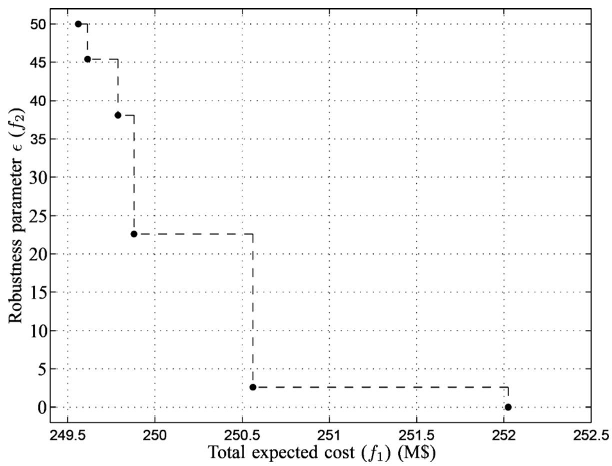


Fig. 5. Pareto front found using the proposed multi-objective formulation for the second case.

TABLE IX
SOLUTIONS FOUND USING THE PROPOSED MULTI-OBJECTIVE FORMULATION FOR THE SECOND CASE

Robustness parameter ϵ	Total expected cost f_1 (10^6\$)	Robustness probability f_2 (%)	Time (s)
50.0%	249.561	50.0	6
49.9%	249.602	45.4	25
45.3%	249.788	38.1	3
38.0%	249.880	22.6	7
22.5%	250.562	2.6	140
2.5%	252.025	$<$ 0.1	600

All solutions found built new substations, rather than expanding the capacity of the existing substations, except for the solution with the best robustness probability, which reinforced the substations at nodes 2 and 3. The results show that the combined capacity of the substations increased as the value of f_2 decreased, i.e., as the robustness of the solution increased.

IV. CONCLUSION

A novel mixed-integer second-order cone programming model for the robust multi-stage substation expansion planning problem considering stochastic demand was presented. The proposed formulation defines the substation expansion alternatives (the construction of new substations and the reinforcement of existing substations) and determines the service area of the substations.

The multi-stage representation allows the distribution system operator to coordinate the substation investments throughout several stages within a planning horizon. The developed mathematical model is robust and considers the effect of stochastic loads on the capacity limits of the substations. Chance constraints were developed in order to guarantee that the substation capacity limits are satisfied with a given robustness probability.

A multi-objective formulation for the substation expansion planning problem was developed considering the investment cost and the robustness of the expansion plan as conflicting objectives. It was proposed a procedure that makes it possible to generate the Pareto front for the problem.

TABLE X
CAPACITY OF THE SUBSTATIONS FOR THE SECOND CASE

Robustness probability f_2 (%)	Capacities of the substations (MVA)
50.0	90, 60, 30, 30, 30, 45, 15, 45, 15
45.4	90, 60, 30, 30, 30, 60, 30, 45, 15
38.1	90, 60, 30, 30, 30, 60, 15, 45, 15
22.6	90, 60, 30, 30, 30, 45, 30, 45, 15
2.6	90, 60, 30, 30, 30, 75, 30, 45, 15
$<$ 0.1	90, 90, 45, 30, 30, 75, 30, 60, 0

The solutions for the substation expansion planning problem for the test cases were found using commercial solvers. The optimal solution of the proposed mixed-integer second-order cone programming model is guaranteed by the classical optimization techniques employed.

Results found for the test systems demonstrated the efficiency and the robustness of the proposed mathematical formulation. The multi-objective representation of the substation expansion planning problem can be used by distribution system operators to choose a suitable solution that considers both the expansion cost and the robustness of the expansion solution.

APPENDIX A
CHANCE CONSTRAINED PROGRAMMING

Consider a linear programming model (29)–(30):

$$\min c^T x \tag{29}$$
$$\text{Subject to}: Ax \leq b. \tag{30}$$

If A has random coefficients such that its rows follow a normal distribution probability with mean $\hat{A}_i$ and covariance matrix $\Sigma_i (A_i = N(\hat{A}_i, \Sigma_i))$, then a chance constrained linear programming model can be formulated as shown in (31)–(32)(see [25]):

$$\min c^T x \tag{31}$$
$$\text{Subject to}: \ \text{Prob}\{Ax \leq b\} \geq 1 - \epsilon. \tag{32}$$

A solution for this problem is ϵ-reliable if it satisfies (32). The difference between (29)–(30) and (31)–(32) is that, in the second formulation, the constraints are modeled as chance constraints, that is, the constraints must be satisfied within a pre-established probability defined by the robustness parameter ϵ. Assuming that there is no correlation between the rows of matrix A, (32) can be written as (33):

$$\text{Prob}\left\{A_i^T x \leq b_i\right\} \geq 1 - \epsilon \quad \forall i = 1, \ldots, \text{Rank}(A). \tag{33}$$

In [25], it is demonstrated that (33) can be represented as the second-order cone constraint (34) if $\psi(\epsilon) > 0$ and $\epsilon > 1/2$. The function $\psi(\epsilon)$ represents the normalized Z-value corresponding to the area under the normal distribution curve for the percentile $1 - \epsilon$. Smaller values of ϵ cause $\psi(\epsilon)$ to become larger, making (34) harder to satisfy. The term $\psi(\epsilon)\sqrt{x^T \Sigma x}$ can be interpreted as a risk term, while $\hat{A}_i^T x$ is the mean value [25]:

$$\hat{A}_i^T x + \psi(\epsilon)\sqrt{x^T \Sigma x} \leq b_i \ \forall i = 1, \ldots, \text{Rank}(A). \tag{34}$$

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