IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 8 November 2022, accepted 1 December 2022, date of publication 5 December 2022, date of current version 27 July 2023.

*Digital Object Identifier 10.1109/ACCESS.2022.3226695*

RESEARCH ARTICLE

# Developing a Robust Expansion Planning Approach for Transmission Networks and Privately-Owned Renewable Sources

**LI PENG[1], ALIREZA ZABIHI[2], MAHDI AZIMIAN[3], HADIS SHIRVANI[3], AND FARHAD SHAHNIA[4]**

[1]Key Laboratory for Energy Monitoring and Edge Computing of Smart City, Hunan City University, Yiyang 413002, China
[2]Department of Electrical Engineering, Islamic Azad University, Najafabad Branch, Isfahan 8514143131, Iran
[3]Department of Electrical and Computer Engineering, Islamic Azad University, Kashan Branch, Kashan 8715998151, Iran
[4]Discipline of Engineering and Energy, Murdoch University, Perth, WA 6150, Australia

Corresponding author: Farhad Shahnia (F.Shahnia@murdoch.edu.au)

**ABSTRACT** Power system restructuring has changed transmission expansion planning (TEP) and caused many complications due to conflicting and contradictory objectives. The transmission capacity expansion would significantly affect the revenue of investor-owned renewable energy sources (RESs). Thus, the investment decisions on merchant RESs must be considered in the TEP studies conducted by the transmission system operator (TSO). In this regard, this paper aims to propose a multi-objective co-planning of investment in transmission networks and merchant RESs with three objective functions: minimizing the investment cost of newly deployed transmission lines, minimizing transmission congestion cost, and minimizing load curtailment in N-1 conditions. Moreover, the TSO guarantees a desirable rate of return for private investors to finance renewable energy projects. Further, a robust optimization (RO) technique is employed to cope with the uncertainties associated with demand and renewable energy production. Also, a posteriori multi-objective optimization algorithm, i.e., the non-dominated sorting genetic algorithm (NSGAII), is applied to solve the advanced optimization problem, followed by the fuzzy min-max method to acquire the final optimal solution. Finally, the IEEE RTS 24-bus test system is utilized to demonstrate the effectiveness and applicability of the suggested approach.

**INDEX TERMS** Transmission expansion planning, renewable energy sources, robust optimization, multi-objective, private investor, uncertainties.

## NOMENCLATURE

### A. SETS AND INDICES

| | |
|---|---|
| $L, L^+$ | Sets of existing and candidate lines, respectively, indexed by $l$. |
| $E$ | Set of representative days, indexed by $e$. |
| $T$ | Set of time intervals of a day, indexed by $t$. |
| $N$ | Set of network buses, indexed by $n$. |
| $G$ | Set of generation units, indexed by $g$. |
| $I$ | Set of candidate buses for installing renewable units, indexed by $i$. |
| $\Phi$ | Set of contingencies, indexed by $k$. |
| $s(l), r(l)$ | Indices of sending and receiving buses of line $l$. |

The associate editor coordinating the review of this manuscript and approving it for publication was Siqi Bu.

### B. PARAMETERS AND CONSTANTS

| | |
|---|---|
| $c_l$ | Investment cost of line $l$. |
| $\tau_e$ | Frequency of each representative day $e$. |
| $\aleph$ | The anticipated investment rate of return. |
| $c_i^{re}$ | Investment cost of each renewable unit. |
| $P^{Max}$ | Maximum capacity of each renewable unit. |
| $\Gamma$ | Upper-bound of the investor financing budget. |
| $x_i^{Max}$ | Maximum number of renewable units at candidate bus $i$. |
| $c_g$ | Operation cost of generator unit $g$. |
| $c_n^{sh}$ | Load shedding penalty factor for demand at bus $n$. |
| $c_i^{cu}$ | Curtailment penalty factor for renewable unit $i$ |
| $\overline{P}_{i,t,e}^{RE}$ | Normalized renewable power production at location $i$, time interval |

$t$, and day $e$.

$\overline{D}_{n,t,e}$ Forecasted demand at bus $n$, time $t$, and day $e$.

$B_l$ Susceptance of line $l$.

$M$ Sufficiently large positive number.

$P_l^{Max}$ Maximum power capacity of line $l$.

$P_g^{Max}$ Maximum generation of unit $g$.

$\overline{P}_{n,t,e}^{sh}$ Maximum amount of allowed load shedding of bus $n$, time interval $t$, and day $e$

### C. VARIABLES AND FUNCTIONS

$x_l$ Binary variable linked with the installation of candidate line $l$ that is 1 if line $l$ is installed; 0 otherwise.

$P_{l,t,e}$ Flowing active power through line $l$ during time interval $t$ and day $e$.

$\lambda_{n,t,e}$ The value of the locational marginal price at bus $n$ during time interval $t$ and day $e$.

$LC_{n,t,e}^k$ The value of load curtailment at bus $n$ during contingency $k$, at time interval $t$, and day $e$.

$P_{i,t,e}^{RE}$ Power production of the renewable unit at candidate bus $i$, time interval $t$, and day $e$, and.

$x_i^{re}$ Integer variable representing the number of the installed renewable unit at bus $i$.

$P_{g,t,e}$ Power production of generator $g$ for each time interval $t$ and day $e$.

$P_{n,t,e}^{sh}$ The amount of load shedding at bus $n$ for each time interval $t$ and day $e$.

$\theta_{n,t,e}$ Voltage angle at bus $n$, respectively, for each time interval $t$ and day $e$.

## I. INTRODUCTION

The major aim of deregulation can be briefed as developing a competitive electricity market to maximize the total social welfare of market participants while keeping the power system reliability within an acceptable level [1]. In regulated power systems, the independent system operator (ISO) is responsible for the expansion problem. In contrast, in deregulated power systems, there are several private investors with unlike interests that usually do not follow the common interest [2]. The transmission network has a key function since it must offer a non-discriminatory and contesting atmosphere for all stakeholders. Thus, the deregulation of power systems has raised new concerns in transmission expansion planning (TEP) studies [3].

The authors in [4] provided a comprehensive review of TEP research. The works focused on this area can be categorized based on types of power systems, solving methods, and modeling of uncertainties. The objective of TEP in a regulated environment is to economically provide the future load demand so that reliability constraints would be satisfied as well. However, in the deregulated environment, TEP provides a competitive setting for all investors and preserves power system reliability. For this purpose, multi-objective formulations were proposed in which the social welfare or social cost, the investment expenditure, transmission congestion expenditure, and system reliability were considered as the objectives [5], [6].

A hierarchical optimization model of distribution network planning under active management was proposed considering various aspects such as balanced network loss, line investment, power purchase cost, carbon emission cost, and policy subsidies [7]. References [8] and [9] reviewed different uncertainty handling methods and compared their pros and cons. According to these works, stochastic programming (SP) and robust optimization (RO) techniques are the most common uncertainty-handling methods. The SP method is extensively utilized to model the uncertainties in TEP. Authors in [10] proposed a stochastic TEP model to deal with the uncertainties associated with demand and wind power production. In that study, the aim of the optimization problem is minimizing the total planning cost while satisfying techno-economic constraints. The work in [11] developed a stochastic bi-level TEP problem in which the uncertainties relating to demand and wind power production are modeled by a set of scenarios. Authors in [12] proposed a stochastic risk-based TEP mathematical formulation to mitigate the curtailment of wind power in a highly renewable-penetrated power system. Authors in [13] proposed a stochastic co-planning framework to determine the optimal number of new transmission lines, the optimal capacity of wind farms, and the optimal capacity of wind farm lines. In that study, the uncertainties of demand and wind power production as well as the contingencies, are modeled by defining a set of scenarios. And finally, reference [14] presented a stochastic TEP formulation under the uncertainties of demand and considering the system reliability. In this reference, the expected total planning cost has been minimized to determine the optimal place, number, and type of newly installed transmission lines.

The above-reviewed studies have provided valuable insights into the SP-based TEP models under the uncertainties of demand and wind power production. The main drawback of SP method is its dependence on the availability of historical data to model the uncertainties as random variables with known probability distribution functions, which are often unavailable. In contrast, the RO technique is usually easier to understand and does not require exact information about uncertain parameters such as probability distribution functions. The RO technique models the uncertainties by defining parametric sets with inadequate information considering the lower and upper bounds of uncertain parameters; so that to find the best solution associated with the worst-case scenario in a settled interval [15], [16].

In the literature, several studies have proposed RO-based TEP models from various characteristics [17], [18], [19], [20], [21], [22], [23]. Authors in [17] proposed a robust TEP model considering $N-k$ contingency and the uncertainties associated with load and renewable energy production. The optimization problem in that study was reformulated as a mixed-integer linear programming model using the duality theory. Reference [18] developed a new multi-stage robust TEP problem to cope with the uncertainties of demand and wind power generation. A two-stage TEP problem was formulated in [19] that has modeled long-term uncertainties of peak demand and generation capacity as well as short-term uncertainties of demand and renewable power generation employing the RO technique. In [20], a two-stage robust TEP framework was developed to determine the worst-case operating expense under demand and generation capacity uncertainties. Also, the correlation between uncertainties was considered via an ellipsoidal uncertainty set using the variance-covariance matrix. Authors in [21] proposed a non-linear bi-level optimization model for robust TEP problems considering the uncertainties of renewable generation and demand. The proposed model in this reference utilized a convex relaxation and was solved using the Benders decomposition method. Authors in [22] proposed a three-level mixed-integer robust TEP model in which the third level was substituted with the KKT optimality conditions, and the resulting bi-level problem was solved using a cutting plane decomposition algorithm. Authors in [23] developed a robust adaptive TEP considering long-term (demand growth) and short-term (such as wind/solar power production) uncertainties. The proposed problem was solved using the tailored implementation of the primal benders' decomposition algorithm.

Moreover, several studies have focused on the RO-based co-planning of transmission networks and renewable energy sources (RESs) [24], [25], [26], [27], [28]. A three-level optimization model was advanced in [24] to find the optimal expansion of robust transmission and renewable generation planning problems. Then, the original problem was transferred into a bi-level problem to solve the optimization problem using the Benders decomposition method. Authors in [25] proposed a dynamic co-planning problem for expanding transmission networks and renewable generation based on a three-level adaptive RO method. Authors in [26] proposed a two-stage min-max-min optimization problem to determine the optimal transmission network expansion and renewable generation capacity in the worst-case scenario. Reference [27] proposed a robust transmission and renewable merchant expansion model. In this reference, the authors developed a three-level optimization problem that minimizes the investment cost of transmission lines and DERs, determines the worst-case scenario, and minimizes the operation cost in the upper, middle, and lower levels. An adaptive two-stage min-max-min RO model was formulated in [28] to determine the optimal expansion development of renewable units and transmission networks. References. [29] has proposed a robust model for joint transmission network and energy storage systems expansion co-planning in which nested column and constraint generation algorithm was employed to solve the optimization problem. And finally, a robust co-planning framework to determine the investment decisions of the transmission network and energy storage expansion planning from the perspective of the transmission system operator (TSO) has been presented in [30].

Table 1 reports a summary of the related research works and compares them with the proposed co-planning model in this paper in terms of the optimization problem, uncertainty modeling, RES planning, considering private investors, and considering reliability criteria. In this table, SO and MO are the abbreviations for single-objective and multi-objective optimization problems while SP and RO respectively denote the stochastic programming approach and robust optimization technique. As seen from this table, this paper proposes a multi-objective robust co-planning model to determine the optimum configuration of the transmission network and merchant RESs from the perspective of the TSO. The proposed model provides an optimal TEP to minimize the investment cost of newly added transmission lines, congestion cost, and load curtailment in N-1 conditions. The model also enables policymakers to find the optimal location and size of RESs for incentivizing private investments. In this regard, the model guarantees a minimum value of the rate of return (RoR) for financing renewable energy projects to make them appealing to stakeholders and/or investors. Thus, the proposed model determines the best solution for developing transmission lines and merchant RESs so that TSO can integrate investor-owned RESs to decrease the investment expenditure on new transmission lines. Compared to previous publications that have not considered the profit of renewable generation companies in the model, this work renders the best plan for RESs that guarantees an acceptable RoR for private investors. Moreover, the uncertain parameters pertinent to the system demand and wind production are modeled through the RO technique, and the eventual expansion planning is determined by employing the developed version of the non-dominated sorting genetic algorithm (NSGA-II) and fuzzy min-max scheme. The key contributions of this paper to the research field are:

- Proposing a multi-objective robust co-planning model to determine the optimal expansion planning of the transmission network and merchant RESs.
- Enabling policymakers to find the optimal location and size of RESs to incentivize private investments with a guaranteed RoR.
- Optimizing a three-level multi-objective optimization problem embraces the investment cost of newly installed transmission lines, transmission network congestion cost, and load curtailment in N-1 conditions.

The remainder of this work is structured as follows. Section II presents the general structure of the proposed co-planning problem and the three-level mathematical formulation of the robust multi-objective optimization problem. In the following, the proposed NSGA-II approach and fuzzy min-max method for solving the resulting robust optimization problem are represented in section III. Lastly, simulation results and conclusions are given in sections IV and V, respectively.

**TABLE 1.** Taxonomy of related research works.

| | Optimization problem | Uncertainty modeling | RES planning | Considering private investor | Considering reliability |
|---|---|---|---|---|---|
| [8] | SO | SP | No | No | Yes |
| [9] | SO | SP | No | No | No |
| [10] | SO | SP | No | No | No |
| [11] | MO | SP | Yes | No | No |
| [12] | SO | SP | No | No | Yes |
| [15] | SO | RO | No | No | Yes |
| [16] | SO | RO | No | No | No |
| [17] | SO | RO | No | No | No |
| [18] | SO | RO | No | No | Yes |
| [19] | SO | RO | No | No | Yes |
| [20] | SO | RO | No | No | No |
| [21] | SO | RO | No | No | No |
| [22] | SO | RO | Yes | No | No |
| [23] | SO | RO | Yes | No | No |
| [24] | SO | RO | Yes | No | Yes |
| [25] | SO | RO | Yes | Yes | No |
| [26] | SO | RO | Yes | No | No |
| [27] | SO | RO | Yes | No | No |
| [28] | SO | RO | Yes | No | No |
| This work | MO | RO | Yes | Yes | Yes |

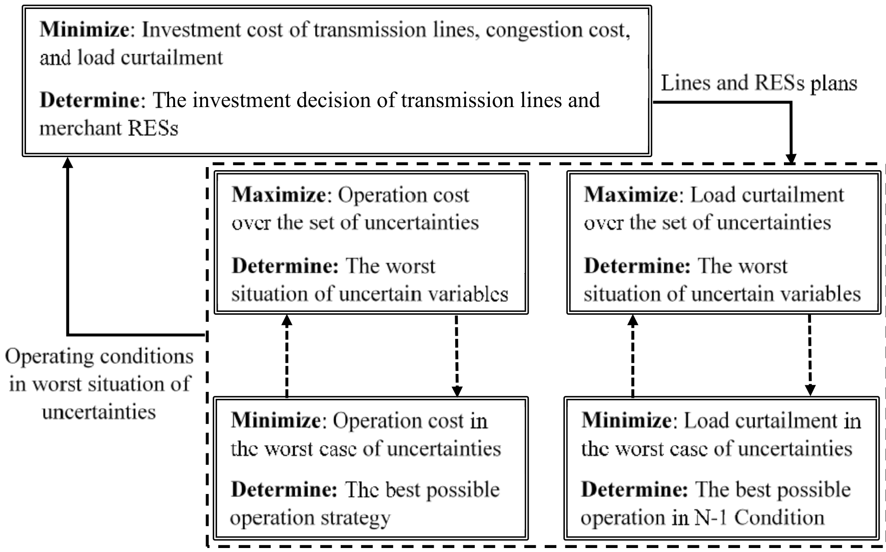



**FIGURE 1.** The general structure of the proposed transmission and RESs co-planning model.

## II. PROBLEM DESCRIPTION AND FORMULATION

Herein, we exhibit the general structure of the suggested robust optimization model, as shown in Figure 1. The presented model is a two-stage three-level optimization problem such that the expansion planning problem for transmission lines and merchant RESs is optimized in the first stage, and the second stage determines the operating strategy of normal and N-1 conditions in the worst-case scenario. In other words, the LMP and power flow of transmission lines in normal conditions and the amount of load curtailment in N-1 conditions are determined in the second stage. In this regard, the worst situations of uncertainties for normal and N-1 conditions are determined in the second level of the problem, and the optimal operation strategies to meet the demand in normal and N-1 conditions are optimized in the third level of the presented optimization problem.

Following this section, the mathematical formulation of the proposed robust multi-objective co-planning problem is described. For this purpose, at first, the deterministic formulation is explained. Then, the model is extended in the second step to consider uncertainties via the robust optimization method.

### A. DETERMINISTIC MODEL

The proposed deterministic planning model is a bi-level optimization problem wherein the upper-level (UL) model determines the newly added lines and installed RES units by minimizing the investment expenditure of newly added lines, total transmission congestion expenditure, and total load curtailment during contingencies over the expansion period. The lower-level (LL) problem runs the market-clearing problem to attain the locational marginal prices (LMPs) and operational status of the power system as well as N-1 conditions to determine load curtailment during contingencies.

### 1) UPPER-LEVEL PROBLEM

The major driving force behind any investment decision in planning studies is the cost of new equipment [31]. Minimizing total investment cost is a classical objective in planning problems [32]. Thus, the primary purpose of the suggested model is to minimize the overall expansion costs:

$$Min.LIC = \sum_{l \in L^+} c_l x_l \tag{1}$$

where $L^+$ is the set of candidate lines indexed by $l$, $c_l$ is the investment cost of line $l$, and $x_l$ is the binary variable linked with the installation of candidate line $l$ that is 1 if line $l$ is installed; 0 otherwise.

Moreover, transmission congestion mitigation in power systems contributes considerably to providing a competitive and non-discriminatory environment for market participants [1]. Any form of congestion and constraints in a transmission system could influence the competition between market participants. For this reason, the power system operators (e.g., TSOs in this work) are responsible for planning the power systems with the aim of mitigating transmission congestion by installing new lines to prevent the creation of market power in the network. Thus, the second objective function is defined as minimizing the total congestion cost:

$$Min.TCC = \sum_{e \in E} \tau_e \sum_{t \in T} \sum_{l \in L \cup L^+} P_{l,t,e} \cdot \left(\lambda_{r(l),t,e} - \lambda_{s(l),t,e}\right) \tag{2}$$

where $P_{l,t,e}$ and $\lambda_{n,t,e}$ that represent the flowing power through line $l$ and the LMPs are calculated by solving the LL problem.

Besides, the power system planner's duty is to improve power system security to provide a reliable environment for the stakeholders and encourage private investors to invest in power systems. Thus, the suggested model's third objective is to minimize the load curtailment in N-1 conditions as a reliability index [33], [34]. The mathematical model of the suggested problem is as follows.

$$Min.TLC = \sum_{e \in E} \tau_e \sum_{t \in T} \sum_{k \in \Phi} \sum_{n \in N} LC_{n,t,e}^k \tag{3}$$

The UL problem is bounded by a set of constraints as follows.

$$\sum_{e \in E} \tau_e \sum_{t \in T} \sum_{i \in \Psi^I} P_{i,t,e}^{RE} \lambda_{i,t,e} \geq \aleph \sum\nolimits_{i \in \Psi^I} c_i^{re} x_i^{re} P^{Max} \tag{4}$$

$$\sum_{i \in \Psi^I} c_i^{re} x_i^{re} P^{Max} \leq \Gamma \tag{5}$$

$$x_i^{re} \leq x_i^{Max} \tag{6}$$

Constraint (4) reflects the expected profit of RES investors in zone $\Psi^I$ over the planning period based on the anticipated investment RoR $\aleph$. Constraints (5) and (6) restrict the upper bound of the investor financing budget and the maximum number of RES units ($x_i^{Max}$), respectively [27].

### 2) LOWER-LEVEL PROBLEM

The LL problem performs the market-clearing problem and the operation of the power system in N-1 conditions for each representative day [27]. Thus, the LL problem is considered as two sets of subproblems associated with normal and N-1 operating conditions.

- Subproblem 1 (SP1):

The objective of SP1, i.e., LL problem in the normal operating situation, for each representative day $e$ is as:

$$\min_{\Lambda_{\mathrm{NLL}}} Z_e^N = \sum_{t \in T} \left( \sum_{g \in \mathrm{G}} c_g P_{g,t,e} + \sum_{n \in \mathrm{N}} c_n^{sh} P_{n,t,e}^{sh} + \sum_{i \in I} c_i^{cu} \left( x_i^{re} P^{Max} \bar{P}_{i,t,e}^{RE} - P_{i,t,e}^{RE} \right) \right) \tag{7}$$

where $\Lambda_{\mathrm{NLL}} = \left\{ P_{g,t,e}, P_{n,t,e}^{sh}, P_{i,t,e}^{RE}, P_{l,t,e}, \theta_{n,t,e} \right\}$ represents the set of decision variables for SP1. The foremost term in (7) is the generator's operation cost, whereas the second and third terms represent the load shedding and renewable energy curtailment penalty. Note that the $x_i^{re}$ is a parameter in the LL problem and is resolved in the UL problem. The constraints of SP1 $\forall t \in T$ and $e \in E$ are as follows.

$$\sum_{g=n} P_{g,t,e} + \sum_{i=n} P_{i,t,e}^{RE} - \sum_{s(l)=n} P_{l,t,e} + \sum_{r(l)=n} P_{l,t,e} + P_{n,t,e}^{sh} = \overline{D}_{n,t,e}; \ \left(\lambda_{n,t,e}\right) \quad \forall \in N \tag{8}$$

$$P_{l,t,e} - B_l \left(\theta_{s(l),t,e} - \theta_{r(l),t,e}\right) = 0; \quad \forall l \in L \tag{9}$$

$$-\left(1 - x_l\right) M \leq P_{l,t,e} - B_l \left(\theta_{s(l),t,e} - \theta_{r(l),t,e}\right) \leq \left(1 - x_l\right) M; \quad \forall l \in L^+ \tag{10}$$

$$-P_l^{Max} \leq P_{l,t,e} \leq P_l^{Max}; \quad \forall l \in L \tag{11}$$

$$-x_l P_l^{Max} \leq P_{l,t,e} \leq x_l P_l^{Max}; \quad \forall l \in L^+ \tag{12}$$

$$0 \leq P_{g,t,e} \leq P_g^{Max}; \quad \forall g \in G \tag{13}$$

$$0 \leq P_{n,t,e}^{sh} \leq \overline{P}_{n,t,e}^{sh}; \quad \forall n \in N \tag{14}$$

$$0 \leq P_{i,t,e}^{RE} \leq x_i^{re} P^{Max} \bar{P}_{i,t,e}^{RE}; \quad \forall i \in I \tag{15}$$

In the above equations, constraint (8) ensures the load balance of each bus provided by producers, neighboring transmission lines, and renewable units. The DC line power flows for existing and new lines are bounded in (9) and (10) [35], [36]. The reason behind considering the DC power flow equations in the proposed planning model is related to its computational efficiency. It is worth mentioning that the computational burden of DC power flow is significantly less than AC and linearized AC power flow models [37], [38]. Moreover, since the X/R ratio in the transmission level of power systems is very high, employing the DC power flow model can be an efficient approach in TEP studies [39]. Besides, the line flow constraints for existing and new transmission lines are given in (11) and (12). Generation capacity, allowable load shedding, and renewable power production bounds are represented in (13) and (15). Note that the dual variable of power balance constraint (8) is the LMP at bus $n$.

- Subproblem 2 (SP2):

In addition to the normal operation condition, the suggested model checks the operation of the reinforced power grid for N-1 outages in the LL problem. The objective of the LL problem in the N-1 operating situation (SP2) for each representative day $e$ and contingency $k$ is as:

$$\min_{\Lambda_{\mathrm{NLL}}} Z_{e,k}^{E} = \sum_{t \in T} \sum_{n \in N} LC_{n,t,e}^{k} \tag{16}$$

The constraints of SP2 are the same as (8)–(15) while considering the outage of component $k$. Moreover, $\Lambda_{\mathrm{ELL}}$ is the set of decision variables of SP2.

### B. ROBUST TEP MODEL

The RO method initially proposed by Soyster [40] is one proper way to model uncertainties in lieu of probabilistic [41] and fuzzy methods [42]. This method does not require the distribution function of uncertain variables and only requires their bounds. Thus, it is applicable when there is insufficient information about uncertain parameters [8]. This method determines the worst-case scenario in the defined bound and tries to attain the best solution immunizing against the worst case.

In this work, the normalized power production of RESs and the demand of the power system are considered uncertain parameters denoted as the set $U = \left\{\widetilde{P_{i,t,e}^{RE}}, \widetilde{D_{n,t,e}}\right\}$, respectively, such that the expected values are available. Without loss of generality, presume that the deviation range of uncertain parameters is symmetrically constrained as follows [43]:

$$\begin{aligned} &\widetilde{P_{i,t,e}^{RE}} \in \left[(1-\alpha_p)\overline{P}_{i,t,e}^{RE}, (1+\alpha_p)\overline{P}_{i,t,e}^{RE}\right]; \\ &\qquad \forall i \in I, \quad t \in T, e \in E \end{aligned} \tag{17}$$

$$\begin{aligned} &\widetilde{D_{n,t,e}} \in \left[(1-\alpha_d)\,\overline{D}_{n,t,e}, (1+\alpha_d)\,\overline{D}_{n,t,e}\right]; \\ &\qquad \forall n \in N, \quad t \in T, \quad e \in E \end{aligned} \tag{18}$$

where $\alpha_p$ and $\alpha_d$ denote the variation range of renewable power production and system demand uncertainties, respectively. According to the RO method, the subproblems SP1 and SP2 are reformulated to capture the worst realization of uncertain parameters in the defined bounds. In other words, the values of uncertainties ($\widetilde{P_{i,t,e}^{RE}}$ and $\widetilde{D_{n,t,e}}$) in the defined ranges should be selected in a way that the objective values of SP1 and SP2 would be maximized. Consequently, the deterministic SP1 and SP2 described in the previous subsection are transformed into the proposed robust subproblems RSP1 and RSP2.

RSP1:

$$\max_{U} \min_{\Lambda_{\mathrm{NLL}}} Z_e^N; \quad \forall e \in E \tag{19}$$

Subject to:

$$(8)-(15)\ \&\ (17)-(18) \tag{20}$$

RSP2:

$$\max_{U} \min_{\Lambda_{\mathrm{NLL}}} Z_{e,k}^{E}; \quad \forall e \in E, \quad k \in \Phi \tag{21}$$

Subject to:

$$(8)-(15)\ \&\ (17)-(18) \tag{22}$$

Note that $\overline{P}_{i,t,e}^{RE}$ and $\overline{D}_{n,t,e}$ in equations (7), (8), and (15) associated with the RSP1 and RSP2 are replaced with $P_{i,t,e}^{\widetilde{RE}}$ and $\widetilde{D_{n,t,e}}$, respectively. Equations (19)-(22) represent that RSP1 and RSP2 should be solved twice. First, fixing the uncertain parameters in set $U$ and solving the minimization problem and determining the variables $\Lambda_{NLL}$ and $\Lambda_{ELL}$. In the next step, fixing the values of $\Lambda_{NLL}$ and $\Lambda_{ELL}$ and solving the maximization problem to obtain $U$.

## III. SOLUTION TECHNIQUE

The suggested robust co-planning model is a multi-objective three-level mixed-integer non-linear programming problem. Such models are generally hard to solve due to the nonlinearity and integer variables. In addition, finding the worst-case scenario makes the model more challenging to solve. Therefore, this paper employs the non-dominated sorting genetic algorithm (NSGAII) approach to solve the optimization problem. The fuzzy min-max method is presented to obtain the final optimal solution.

Figure 2 shows the flowchart of the proposed NSGAII-based approach followed by the fuzzy min-max method to solve the proposed co-planning model. According to the figure, at first, the initial population (i.e., a set of added lines and installed renewable units) is randomly created in the domain of solutions. Then, for each member of the population, the investment cost of transmission lines are calculated. In the next step, the values of $\alpha_d$ and $\alpha_p$ are set equal to 0 and then the values of uncertain parameters $\tilde{D}_{n,t,e}$ and $\widetilde{P_{i,t,e}^{RE}}$ are calculated. Then, the RSP1 and RSP2 are solved by fixing the values of uncertain parameters to determine the minimum congestion costs and load curtailment in N-1 conditions. After that, the values of $\alpha_d$ and $\alpha_p$ are increased gradually by 0.001 to $\alpha_d^{max}$ and $\alpha_p^{max}$ and RSP1 and RSP2 are solved for both lower and upper bounds of uncertain parameters, i.e.$(1 \pm \alpha)\,\bar{D}_{n,t,e}$ and $(1 \pm \alpha)\,\tilde{P}_{i,t,e}^{RE}$. Persuading this procedure, the best state of objectives (minimum load curtailment and minimum congestion cost in the worst-case situation) are obtained for each plan. Then, the population is sorted into Pareto fronts on the basis of non-dominancy ranks and the crowding distance of each plan. In the following, the new population is produced based on crossover, mutation, and selection operators. Lastly, the process is iterated for the

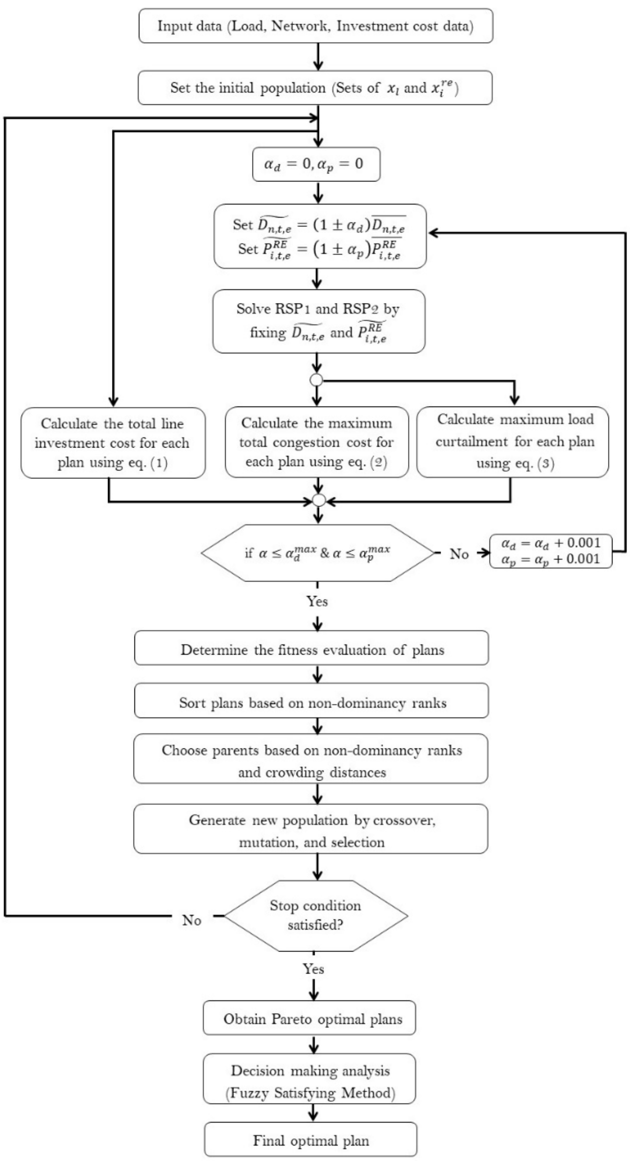



**FIGURE 2. Flowchart of the proposed solution technique.**

new generation until reaching the termination criterion, i.e., the maximum number of iterations and changes in the values of objective functions. It is noteworthy that constraint (4) is regarded in the NSGAII algorithm to penalize the objective function in case of violation.

Furthermore, after determining non-dominated plans, the decision-maker must select the best plan of the Pareto solutions using a decision-making approach because, in the end, planners need an expansion plan, not a set of non-dominated solutions. While there are different decision-making approaches, the fuzzy min-max method is extensively utilized to model the decision-maker's preferences due to its resemblance and simplicity to human personalized rationale [1], [44]. This method enables the decision-makers to obtain the optimal plan among Pareto solutions, especially when the objective functions are not the same type. Hence, the final optimal plan is determined by the fuzzy min-max method in this work. Herein, the linear membership function is assigned to each objective showing the decision-maker's belief (23). Herein, 0 and 1 represent the membership function values for the worst and best Pareto optimal plans, respectively [44].

$$\mu_{f_k}(X) = \begin{cases} 0 & f_k(X) > f_k^{Max} \\ \dfrac{f_k^{Max} - f_k(X)}{f_k^{Max} - f_k^{Min}} & f_k^{Min} \le f_k(X) \le f_k^{Max} \\ 1 & f_k(X) < f_k^{Min} \end{cases} \tag{23}$$

In the second step, the decision-maker is requested to determine the desirable level of objective functions ($\mu_{dk}$). After that, for a certain set of $\mu_{dk}$, the final optimal plan can be attained by solving the following optimization problem.

$$Min \sum_{k=1}^{m} \left|\mu_{dk} - \mu_{f_k}(X)\right|^{p}; X \in Solution\ Set \tag{24}$$

where $1 \le p \le \infty$ and $m$ is the number of objective functions. It can be seen that this technique minimizes the p-norm deviations from the reference membership values.

## IV. PERFORMANCE EVALUATION

This section evaluates the performance of the proposed co-planning model's numerical results based on the IEEE RTS 24-bus test system to validate and demonstrate its applicability and efficacy. The proposed model was implemented on a PC with a Core i7 CPU (clocking at 2.2 GHz) and 6 GB RAM. Besides, the optimization problem was solved using GAMS and MATLAB interfacing with the CPLEX solver in GAMS. In this regard, the upper- and middle-level problems are simulated in MATLAB, while the lower-level problem to determine the LMPs and operational status of the power system as well as N-1 conditions to determine load curtailment during contingencies are modeled using the GAMS software. The population size and the maximum number of iterations for the NSGAII algorithm are assumed to be 300 and 200, respectively. Moreover, we considered the maximum iteration as the stopping criterion.

This study presumes that five private investors invest in separate regions of the test system. Thus, the test system was divided into five separate zones, corresponding to one private investor, as indicated in Figure 3. The transmission lines' capacity of the test system is multiplied by 0.8 so as to better illustrate the advantages of the transmission expansion planning study. The investment and operation data of the test system are taken from [32], [45], and [46]. In addition, it should be noted that we assume up to three new lines can be mounted in each corridor, and the cost of developing ac substations for connecting lines and RES units is included in their investment costs.

Also, we consider four representative days for demand and wind power production in different zones. To determine

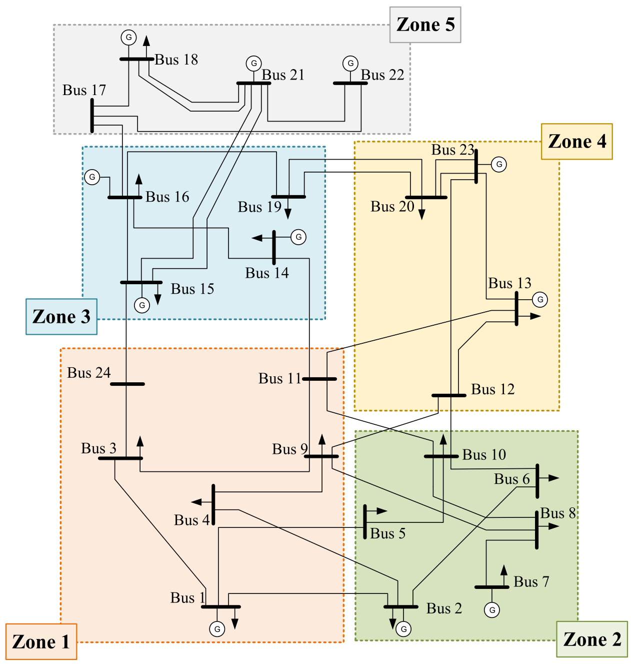



**FIGURE 3.** The IEEE RTS 24-bus with five investors' zones.

the representative days, we employ the K-means clustering method. The hourly forecasted values of normalized demand and wind power production in four representative days are illustrated in Figure 4. The frequency of representative days 1–4 is 111, 83, 61, and 110, respectively. Besides, in this work, we consider the expansion time horizon of ten years, considering a 10% discount rate and 20% acceptable RoR for private investors. In addition, it should be noted that we assume up to three new lines can be mounted in each corridor.

### A. DETERMINISTIC TEP

In this part, the outcomes of the deterministic model are presented after solving (1) - (16) using the predicted loads of the IEEE 24-bus test system. To this end, the presented NSGA-II approach is exerted by 200 populations and 200 iterations to unravel the optimization problem. In this regard, the set of non-dominated solutions was achieved after 116 iterations. The average running time of the deterministic optimization problem is around 260 minutes. The non-dominated solutions are indicated in Figure 5a-c. As can be deduced from the figure, the non-dominated optimal solutions signify a range of the investment expense between \$8.9–\$12.7 million, while the congestion cost is between \$0–\$88 thousand.

Moreover, this figure shows that the load curtailment varies between 0–4000 MW. After determining the trade-off between the objective terms, the planner finds the best expansion schedule by selecting the desired levels of the objectives. In this study, we assumed that the developers select the following desirable levels:

- $\mu_{d1} = 0.9$ : for investment cost

**TABLE 2.** Results of the deterministic model.

| Corridors | No. of Added Lines | RESs expansion plan |
|---|---|---|
| 3-24 | 1 | |
| 6-10 | 2 | Zone 1: RoR=21.6%, 240 MW installed at bus 9 100 MW installed at bus 24 |
| 8-10 | 1 | |
| 10-11 | 1 | |
| 10-12 | 1 | |
| 11-14 | 1 | |
| 14-16 | 1 | Zone 2: RoR=23.2%, 300 MW installed at bus 8 |
| 15-21 | 1 | |
| 15-24 | 1 | |
| 16-17 | 1 | |
| 16-19 | 1 | Zone 4: RoR=20.5%, 150 MW installed at bus 20 |
| 17-18 | 1 | |
| 1-8 | 2 | |
| 14-23 | 2 | |
| **Investment Cost (million dollars)** | | 11.835 |
| **Congestion Cost (thousand dollars)** | | 0 |
| **Load Curtailment (MW)** | | 20 |

**TABLE 3.** Results of the proposed RO model.

| Corridors | No. of Added Lines | RESs expansion plan |
|---|---|---|
| 1-5 | 1 | |
| 3-24 | 1 | Zone 1: RoR=20%, 220 MW installed at bus 9 |
| 6-10 | 2 | |
| 8-9 | 1 | |
| 10-11 | 1 | |
| 11-14 | 1 | |
| 14-16 | 2 | Zone 2: RoR=20.5%, 270 MW installed at bus 8 |
| 15-21 | 1 | |
| 15-24 | 1 | |
| 16-17 | 1 | |
| 16-23 | 1 | |
| **Investment Cost (million dollars)** | | 12.925 |
| **Congestion Cost (thousand dollars)** | | 40 |
| **Load Curtailment (MW)** | | 182 |

- $\mu_{d2} = 0.8$ : for congestion cost
- $\mu_{d3} = 0.8$ : for load curtailment

The final solution is determined using the fuzzy min-max approach mentioned in section III. Table 2 shows the final optimal development plan of the transmission network and RESs and the values of objective functions. As seen in the table, the investment cost, congestion cost, and load curtailment of the final optimal plan are \$11.835 million, \$0, and 20 MW, respectively. Moreover, the table shows that private investors would invest in wind power installation equal to 340 MW in zone 1, 300 MW in zone 2, and 150 MW in zone 4 ($RoR > 20\%$).

### B. ROBUST TEP

RO is a risk management technique presenting a conservative decision for risk-averse investors. Such investors prefer a plan with lower returns than higher ones that are more robust against uncertainties. Thus, we have solved (19)-(22), and Figure 5d-f shows the non-dominated solutions of the optimization for $\alpha_d = \alpha_p = 0.1$. As seen in the figure,

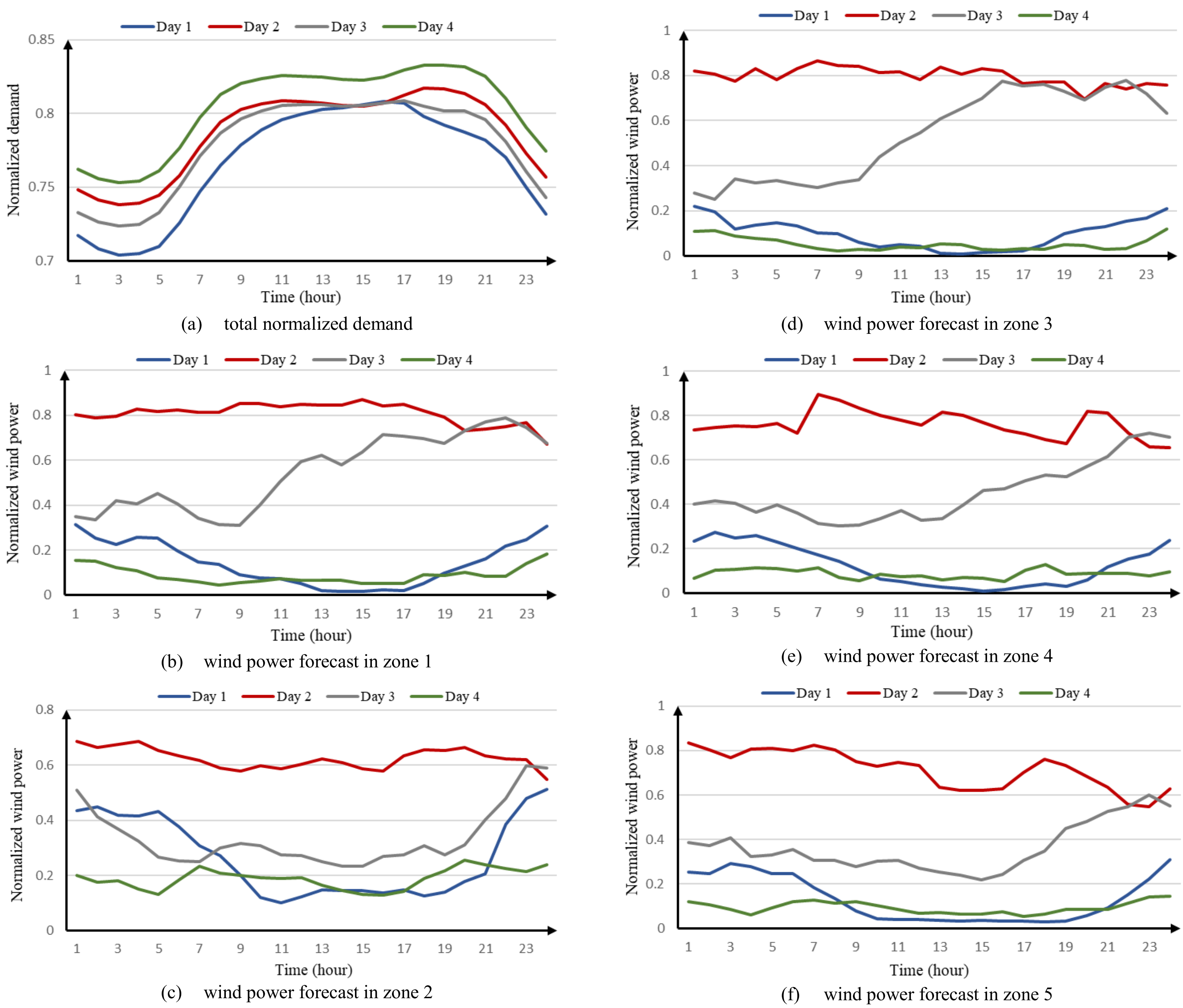



**FIGURE 4.** **The normalized demand and wind power forecasts for different zones.**

the non-dominated optimal solutions for $\alpha_d = \alpha_p = 0.1$ represent a range of investment expenditure between \$8.46–18.7 million, while the congestion expenditure is between \$0–164 thousand. The load curtailment varies between 0–4901 MW in the non-dominated optimum solutions. Besides, the trade-off between investment and congestion expenditures is contradictory, which means that when the amount of investment cost increases, the congestion cost decreases. In other words, the trade-off shows that more investment in transmission line installation would decrease congestion in the transmission network. Additionally, the trade-off trend of investment cost and load curtailment is similar, denoting that more investment in transmission line installation decreases load curtailment. In contrast, less investment in transmission networks increases load curtailment.

The final optimal solution can be determined by assuming the aforementioned desirable levels. Table 3 shows the final optimal solution of the robust co-planning problem for $\alpha_d = \alpha_p = 0.1$. By comparing the results reported in Tables 2 and 3, it can be concluded that employing the RO technique for modeling the uncertain parameters increases the investment cost of newly added lines, the congestion cost, and the load curtailment in the optimal expansion plan. This observation indicates that the RO technique optimizes for the worst-case scenario over the deviation range of uncertain parameters.

To carefully examine the impact of transmission expansion in mitigating wind curtailment, the value of wind production and curtailment in two cases with and without the expansion of the transmission network is illustrated in Figure 6. As inferred from the figure, the wind curtailment would be lessened intensely by installing new transmission lines.

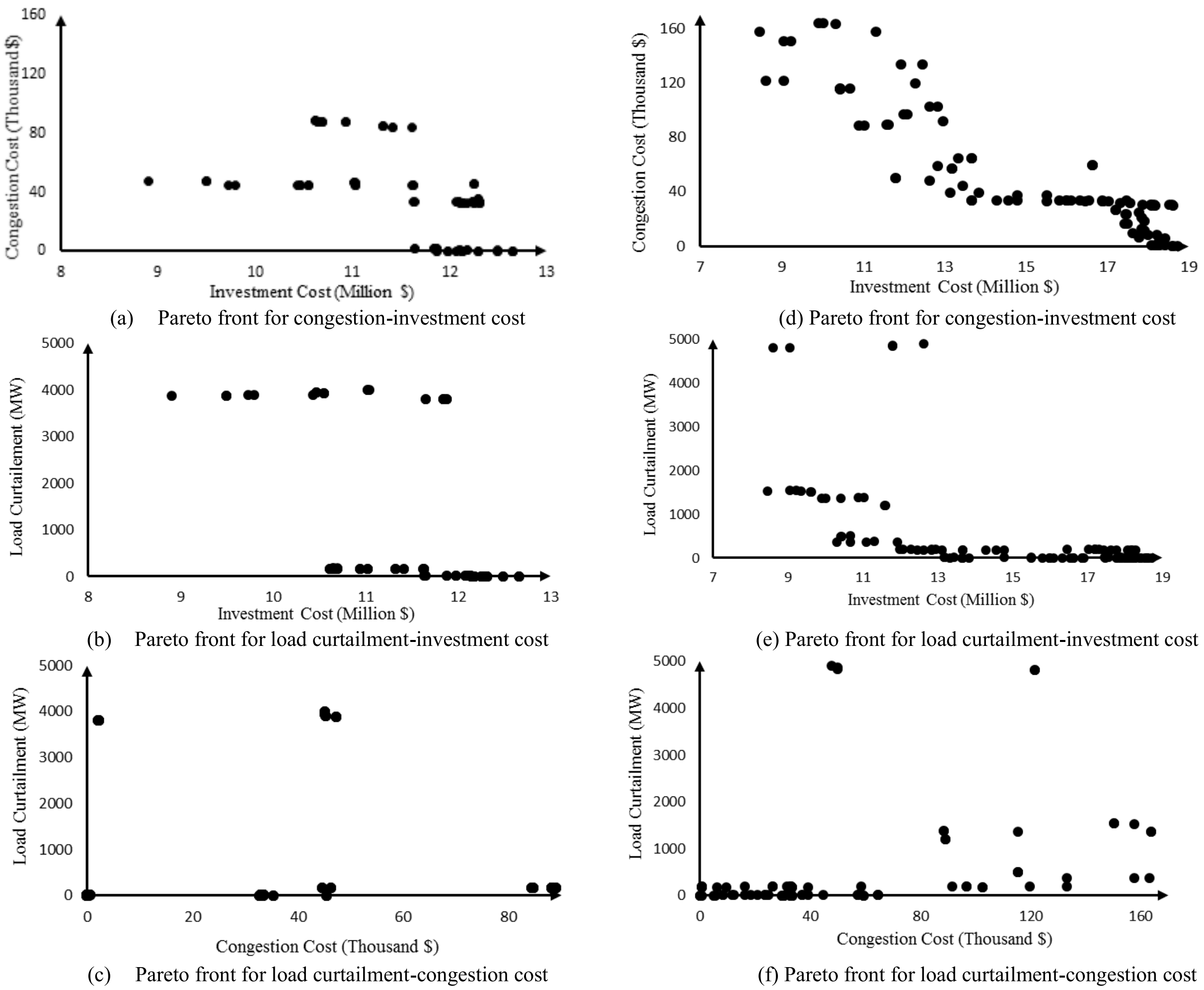



**FIGURE 5.** Non-dominated solutions for the deterministic model (a)–(c) and for the robust model with $\alpha_d = \alpha_p = 0.1$ (d)–(f).

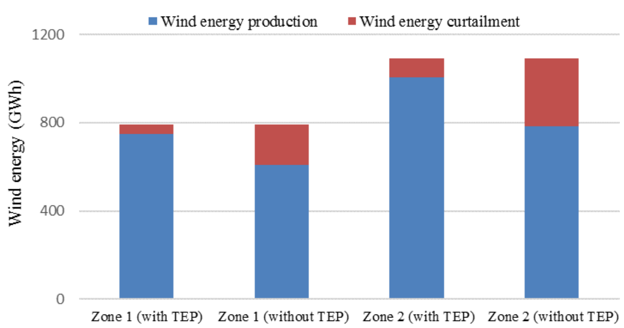



**FIGURE 6.** Wind energy production and curtailment in different cases.

In other words, by capitalizing on the transmission network, the wind energy curtailment decreases by 77.3 and 71.5% in zones 1 and 2, respectively. The result represents the capability of the proposed model in solving the transmission planning problems with high penetration of wind resources.

In addition, to investigate the positive impact of merchant RESs, the proposed robust co-planning problem for transmission networks and merchant RESs is compared with the robust TEP problem. In this regard, Table 4 shows the optimal transmission expansion plan, the investment cost of newly added lines, the congestion cost, and the load curtailment in the above-described cases. This table shows that

**TABLE 4.** Results of the comparative analysis.

| | Proposed model | Robust TEP |
|---|---|---|
| Installed transmission lines (corridor: number) | (1-5):1 | (3-24):1 |
| | (3-24):1 | (6-10):2 |
| | (6-10):2 | (8:10):1 |
| | (8-9):1 | (10-11):1 |
| | (10-11):1 | (10-12):1 |
| | (11-14):1 | (11-14):1 |
| | (14-16):2 | (14-16):2 |
| | (15-21):1 | (12-23):1 |
| | (15-24):1 | (15-21):2 |
| | (16-17):1 | (16-17):1 |
| | (16-23):1 | (16-23):2 |
| Investment cost (million $) | 12.925 | 14.102 |
| Congestion cost (thousand $) | 40 | 45.1 |
| Load curtailment (MW) | 182 | 212 |

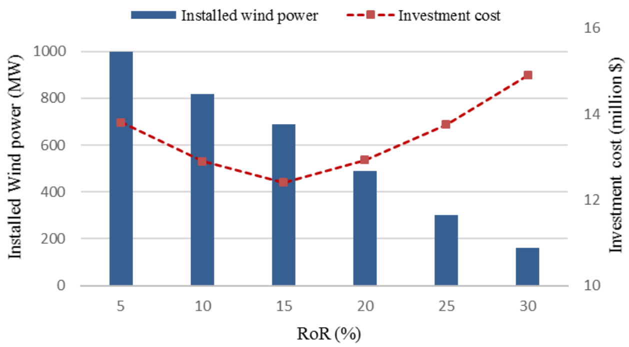



**FIGURE 7.** Installed wind power and investment cost of newly added lines for different RoR.

without employing the merchant RESs, 4 more transmission lines are required to meet the test system's demand optimally. Also, this table indicates that corridors (6-10) and (14-16) with the most installed transmission lines are the vulnerable corridors of the test system in the proposed co-planning and TEP problems, and corridors (15-21) and (16-23) can be called as vulnerable corridors in the TEP problem. Also, several corridors, including (3-24), (6-10), (10-11), (11-14), (14-16), (15-21), (16-17), and (16-23), are among the selected corridors to install new transmission lines in the proposed co-planning and TEP problems which shows the high importance of these corridors. Besides, this table shows that employing merchant RESs in the expansion planning studies improves the network conditions. As inferred from this table, employing merchant RESs along with transmission network expansion decreases the investment cost of added lines by 1.177 million$, the congestion cost by 4100 $, and load curtailment by 30 MW.

In the last step of the simulation study, a sensitivity analysis is conducted to measure the influence of private investors' minimum RoR on wind power's installed capacity and the transmission network's investment expenditure. In this regard, running the proposed robust TEP model, the total capacity of wind farms, and the investment cost of newly added lines for different values of the minimum RoR are determined and illustrated in Figure 7. As seen in the figure, when the acceptable RoR of private investors decreases, the capacity of wind power generation increases. Besides, the figure shows that the minimum investment cost of transmission networks occurs when the RoR equates to 15%. When the RoR significantly decreases (for instance, $RoR = 5\%$), the TSO would invest in more installation of new transmission lines with higher penetration of wind power so as to mitigate wind curtailment. On the other hand, with increasing the RoR (for instance, $RoR = 30\%$), the capacity of wind power decreases in the grid. Thus, the TSO decides to strengthen the transmission network so as to decrease load curtailment and congestion costs.

### C. COMPUTATIONAL COMPLEXITY

The computational complexity of the proposed co-planning model is characterized in this section by the number of constraints and variables. Table 5 shows the number of constraints and variables for the RSP1 and RSP2 optimization problems based on the number of buses ($n_B$), generator units ($n_G$), existing and candidate lines ($n_L$ and $n_{L^+}$, RES units ($n_I$), time intervals ($n_T$), representative days ($n_E$) and contingencies ($n_k$). As illustrated in this table, the number of time intervals, representative days, and contingencies have the most impact on the solution time of the problem. However, both RSP1 and RSP2 can be decomposed and solved for each of them. Hence, the number of subproblems would increase for larger test systems. It should be noted that the number of decision variables for the upper-level problem (decision variable for NSGAII algorithm) is $n_{L^+} + n_I$. Moreover, we utilize the $\alpha_d$ and $\alpha_p$ parameters for realizing the worst-case situation of uncertainties that increases the number of times that RSP1 and RSP2 will be solved.

**TABLE 5.** Computational complexity of the proposed planning model.

| | RSP1 | RSP2 |
|---|---|---|
| # of constraints | $n_T n_E(1+2n_B+n_G+3n_L+3n_{L^+}+n_I)$ | $n_T n_E n_k(1+2n_B+n_G+3n_L+3n_{L^+}+n_I)$ |
| # of variables | $n_T n_E(n_G+2n_B+n_I+n_L+n_{L^+})$ | $n_T n_E n_k(n_G+2n_B+n_I+n_L+n_{L^+})$ |
| Comp. time (sec) | 1.28 | 2.06 |

## V. CONCLUSION

This paper developed a novel co-planning framework so as to determine the optimal expansion of transmission networks and merchant RESs from the perspective of TSO. The RO method was employed to cope with the uncertainties associated with renewable generation and demand. The suggested problem was formulated as a three-level multi-objective optimization problem. The investment cost of newly added transmission lines, congestion cost, and load curtailment was minimized in the upper-level problem. Besides, the worst-case scenario of uncertainties and the best planning strategy in normal and N-1 conditions were determined in the middle- and lower-level problems, respectively. Finally, the presented multi-objective mixed-integer non-linear programming model was solved utilizing the NSGA-II approach followed by the fuzzy min-max technique to find the optimum solution. The simulation study demonstrated that the optimal expansion schedule of the proposed co-planning framework could effectively improve the network conditions. The numerical results show that employing the merchant RESs with 20% acceptable RoR for private investors in the TEP problem would decrease the investment cost of newly added lines by 8.3%, the transmission network congestion cost by 11.3%, and the load curtailment by 14.2%. Besides, the results confirmed that employing private investors in renewable energy projects with an acceptable RoR of 15% would optimize the investment cost of the installation of new transmission lines. Thus, the optimum value for RoR, considering TSOs and private investors' preferences, would be 15%.

Future works can focus on developing a co-planning framework for transmission networks and RESs, considering the impact of different penetration levels of distributed energy resources on the optimal expansion plan. Further, future research works can focus on mitigating the computational burden of the proposed optimization problem for large-scale power systems. In this regard, decomposition techniques and constraint reduction algorithms can be applied to large-scale power systems to improve the computational performance of the proposed model.

## REFERENCES

[1] P. Maghouli, S. H. Hosseini, M. O. Buygi, and M. Shahidehpour, "A multi-objective framework for transmission expansion planning in deregulated environments," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 1051–1061, May 2009.

[2] P. V. Gomes and J. T. Saraiva, "State-of-the-art of transmission expansion planning: A survey from restructuring to renewable and distributed electricity markets," *Int. J. Electr. Power Energy Syst.*, vol. 111, pp. 411–424, Oct. 2019.

[3] Y. Tohidi and M. R. Hesamzadeh, "Multi-regional transmission planning as a non-cooperative decision-making," *IEEE Trans. Power Syst.*, vol. 29, no. 6, pp. 2662–2671, Nov. 2014.

[4] M. Mahdavi, C. S. Antunez, M. Ajalli, and R. Romero, "Transmission expansion planning: Literature review and classification," *IEEE Syst. J.*, vol. 13, no. 3, pp. 3129–3140, Sep. 2018.

[5] A. Arabali, M. Ghofrani, M. Etezadi-Amoli, M. S. Fadali, and M. Moeini-Aghtaie, "A multi-objective transmission expansion planning framework in deregulated power systems with wind generation," *IEEE Trans. Power Syst.*, vol. 29, no. 6, pp. 3003–3011, Nov. 2014.

[6] X. Xu, D. Niu, B. Xiao, X. Guo, L. Zhang, and K. Wang, "Policy analysis for grid parity of wind power generation in China," *Energy Policy*, vol. 138, Mar. 2020, Art. no. 111225.

[7] X. Xu, D. Niu, L. Peng, S. Zheng, and J. Qiu, "Hierarchical multi-objective optimal planning model of active distribution network considering distributed generation and demand-side response," *Sustain. Energy Technol. Assessments*, vol. 53, Oct. 2022, Art. no. 102438.

[8] H. Mazaheri, H. Ranjbar, H. Saber, and M. Moeini-Aghtaie, "Expansion planning of transmission networks," in *Uncertainties in Modern Power Systems*. Amsterdam, The Netherlands: Elsevier, 2021, pp. 35–56.

[9] A. Soroudi and T. Amraee, "Decision making under uncertainty in energy systems: State of the art," *Renew. Sustain. Energy Rev.*, vol. 28, pp. 376–384, Dec. 2013.

[10] A. A. Ghadimi, M. Amani, M. Bayat, S. Ahmadi, M. R. Miveh, and F. Jurado, "Stochastic transmission expansion planning in the presence of wind farms considering reliability and N-1 contingency using grey wolf optimization technique," *Electr. Eng.*, vol. 104, no. 2, pp. 727–740, Apr. 2022.

[11] T. Barforoushi and R. Heydari, "Risk constrained transmission expansion planning in electricity markets considering wind curtailment cost," *Iranian J. Electr. Electron. Eng.*, p. 2247, 2022.

[12] D. Liu, S. Zhang, H. Cheng, L. Liu, J. Zhang, and X. Zhang, "Reducing wind power curtailment by risk-based transmission expansion planning," *Int. J. Electr. Power Energy Syst.*, vol. 124, Jan. 2021, Art. no. 106349.

[13] M. Taherkhani, S. H. Hosseini, M. S. Javadi, and J. P. S. Catalão, "Scenario-based probabilistic multi-stage optimization for transmission expansion planning incorporating wind generation integration," *Electr. Power Syst. Res.*, vol. 189, Dec. 2020, Art. no. 106601.

[14] S. Alaee, R. A. Hooshmand, and R. Hemmati, "Stochastic transmission expansion planning incorporating reliability solved using SFLA meta-heuristic optimization technique," *CSEE J. Power Energy Syst.*, vol. 2, no. 2, pp. 79–86, Jun. 2016.

[15] S. Dehghan, N. Amjady, and A. J. Conejo, "Adaptive robust transmission expansion planning using linear decision rules," *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 4024–4034, Sep. 2017.

[16] H. Saber, H. Ranjbar, M. Ehsan, and A. Anvari-Moghaddam, "Transactive charging management of electric vehicles in office buildings: A distributionally robust chance-constrained approach," *Sustain. Cities Soc.*, vol. 87, Dec. 2022, Art. no. 104171.

[17] Z. Wu, Y. Liu, W. Gu, Y. Wang, and C. Chen, "Contingency-constrained robust transmission expansion planning under uncertainty," *Int. J. Electr. Power Energy Syst.*, vol. 101, pp. 331–338, Oct. 2018.

[18] S. Dehghan, N. Amjady, and A. J. Conejo, "A multistage robust transmission expansion planning model based on mixed binary linear decision rules—Part I," *IEEE Trans. Power Syst.*, vol. 33, no. 5, pp. 5341–5350, Sep. 2018.

[19] Á. García-Cerezo, L. Baringo, and R. García-Bertrand, "Robust transmission network expansion planning considering non-convex operational constraints," *Energy Econ.*, vol. 98, Jun. 2021, Art. no. 105246.

[20] C. Roldan, R. Minguez, R. Garcia-Bertrand, and J. M. Arroyo, "Robust transmission network expansion planning under correlated uncertainty," *IEEE Trans. Power Syst.*, vol. 34, no. 3, pp. 2071–2082, May 2019.

[21] N. Y. Puvvada, A. Mohapatra, and S. C. Srivastava, "Robust AC transmission expansion planning using a novel dual-based bi-level approach," *IEEE Trans. Power Syst.*, vol. 37, no. 4, pp. 2881–2893, Jul. 2021.

[22] C. Ruiz and A. J. Conejo, "Robust transmission expansion planning," *Eur. J. Oper. Res.*, vol. 242, no. 2, pp. 390–401, Apr. 2015.

[23] X. Zhang and A. J. Conejo, "Robust transmission expansion planning representing long- and short-term uncertainty," *IEEE Trans. Power Syst.*, vol. 33, no. 2, pp. 1329–1338, Mar. 2017.

[24] J. M. Ramirez, A. Hernandez, and J. A. Marmolejo, "A robust multistage approach to solve the generation and transmission expansion planning problem embedding renewable sources," *Electr. Power Syst. Res.*, vol. 186, Sep. 2020, Art. no. 106396.

[25] C. Roldán, A. A. Sánchez de la Nieta, R. García-Bertrand, and R. Mínguez, "Robust dynamic transmission and renewable generation expansion planning: Walking towards sustainable systems," *Int. J. Electr. Power Energy Syst.*, vol. 96, pp. 52–63, Mar. 2018.

[26] A. Moreira, D. Pozo, A. Street, and E. Sauma, "Reliable renewable generation and transmission expansion planning: Co-optimizing system's resources for meeting renewable targets," *IEEE Trans. Power Syst.*, vol. 32, no. 4, pp. 3246–3257, Jul. 2016.

[27] H. Ranjbar, S. H. Hosseini, and H. Zareipour, "A robust optimization method for co-planning of transmission systems and merchant distributed energy resources," *Int. J. Electr. Power Energy Syst.*, vol. 118, Jun. 2020, Art. no. 105845.

[28] K. Tian, W. Sun, D. Han, and C. Yang, "Coordinated planning with predetermined renewable energy generation targets using extended two-stage robust optimization," *IEEE Access*, vol. 8, pp. 2395–2407, 2019.

[29] S. Wang, G. Geng, and Q. Jiang, "Robust co-planning of energy storage and transmission line with mixed integer recourse," *IEEE Trans. Power Syst.*, vol. 34, no. 6, pp. 4728–4738, Nov. 2019.

[30] X. Zhang and A. J. Conejo, "Coordinated investment in transmission and storage systems representing long- and short-term uncertainty," *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 7143–7151, Nov. 2018.

[31] M. Azimian, V. Amir, and S. Javadi, "Economic and environmental policy analysis for emission-neutral multi-carrier microgrid deployment," *Appl. Energy*, vol. 277, Nov. 2020, Art. no. 115609.

[32] S. Dehghan and N. Amjady, "Robust transmission and energy storage expansion planning in wind farm-integrated power systems considering transmission switching," *IEEE Trans. Sustain. Energy*, vol. 7, no. 2, pp. 765–774, Apr. 2015.

[33] M. Azimian, V. Amir, S. Javadi, S. Mohseni, and A. C. Brent, "Resilience-oriented planning of multi-carrier microgrids under cyber-attacks," *Sustain. Cities Soc.*, vol. 79, Apr. 2022, Art. no. 103709.

[34] O. Rezaei, O. Mirzapour, M. Panahazari, and H. Gholami, "Hybrid AC/DC provisional microgrid planning model considering converter aging," *Electricity*, vol. 3, no. 2, pp. 236–250, Jun. 2022.

[35] R. Habibifar, H. Ranjbar, M. Shafie-Khah, M. Ehsan, and J. P. S. Catalao, "Network-constrained optimal scheduling of multi-carrier residential energy systems: A chance-constrained approach," *IEEE Access*, vol. 9, pp. 86369–86381, 2021.

[36] O. Mirzapour and M. Sahraei-Ardakani, "Environmental impacts of power flow control with variable-impedance FACTS," in *Proc. 52nd North Amer. Power Symp. (NAPS)*, Apr. 2021, pp. 1–6.

[37] Y. Nan, Y. Di, Z. Zheng, C. Jiazhan, C. Daojun, and W. Xiaoming, "Research on modelling and solution of stochastic SCUC under AC power flow constraints," *IET Gener., Transmiss. Distrib.*, vol. 12, no. 15, pp. 3618–3625, Aug. 2018.

[38] R. Habibifar, H. Saber, M. R. K. Gharigh, and M. Ehsan, "Planning framework for BESSs in microgrids (MGs) using linearized AC power flow approach," in *Proc. Smart Grid Conf. (SGC)*, Nov. 2018, pp. 1–7.

[39] M. Qorbani and T. Amraee, "Long term transmission expansion planning to improve power system resilience against cascading outages," *Electr. Power Syst. Res.*, vol. 192, Mar. 2021, Art. no. 106972.

[40] A. L. Soyster, "Convex programming with set-inclusive constraints and applications to inexact linear programming," *Oper. Res.*, vol. 21, no. 5, pp. 1154–1157, Sep. 1973.

[41] H. Li, K. Hou, X. Xu, H. Jia, L. Zhu, and Y. Mu, "Probabilistic energy flow calculation for regional integrated energy system considering cross-system failures," *Appl. Energy*, vol. 308, Feb. 2022, Art. no. 118326.

[42] K. Hamedi, S. Sadeghi, S. Esfandi, M. Azimian, and H. Golmohamadi, "Eco-emission analysis of multi-carrier microgrid integrated with compressed air and power-to-gas energy storage technologies," *Sustainability*, vol. 13, no. 9, p. 4681, Apr. 2021.

[43] N. Rezaei, A. Khazali, M. Mazidi, and A. Ahmadi, "Economic energy and reserve management of renewable-based microgrids in the presence of electric vehicle aggregators: A robust optimization approach," *Energy*, vol. 201, Jun. 2020, Art. no. 117629.

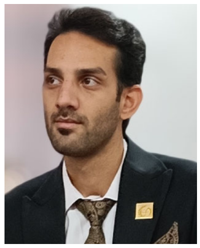
[44] H. Saber, M. Moeini-Aghtaie, M. Ehsan, and M. Fotuhi-Firuzabad, "A scenario-based planning framework for energy storage systems with the main goal of mitigating wind curtailment issue," *Int. J. Electr. Power Energy Syst.*, vol. 104, pp. 414–422, Jan. 2019.

[45] P. Dehghanian, S. H. Hosseini, M. Moeini-Aghtaie, and A. Arabali, "Optimal siting of DG units in power systems from a probabilistic multi-objective optimization perspective," *Int. J. Electr. Power Energy Syst.*, vol. 51, pp. 14–26, Oct. 2013.

[46] C. Grigg, P. Wong, P. Albrecht, R. Allan, M. Bhavaraju, R. Billinton, Q. Chen, C. Fong, S. Haddad, S. Kuruganty, and W. Li, "A report prepared by the reliability test system task force of the application of probability methods subcommittee," *IEEE Trans. Power Syst.*, vol. 14, no. 3, pp. 1010–1020, Aug. 1999.


**LI PENG** received the master's degree from the Changsha University of Science and Technology, China, in 2013. She is currently working with the School of Mechanical and Electrical Engineering, Hunan City University. Her current research interests include power system informatization, intelligent algorithm, and new energy.

**ALIREZA ZABIHI** received the B.Sc. and M.Sc. degrees in electrical engineering from Islamic Azad University, Najafabad Branch, Isfahan, Iran. His research interests include deep learning, machine learning, power systems, renewable energy, and zero energy building.



**MAHDI AZIMIAN** received the Ph.D. degree in electrical engineering from Islamic Azad University, Kashan Branch, Kashan, Iran, in 2021. He was a Research and Development Manager at the University-Industry Collaboration Center, Islamic Azad University. He is currently the CEO of Teta Company, seeking available high-tech equipment and solutions to empower the grid with smart grid technologies. His particular expertise is on the resilient deployment of the grid of the future in the era of smart grid technologies by investigating the role of microgrids, distributed energy resources, demand response, and other emerging technologies.

**HADIS SHIRVANI** received the M.S. degree in electrical engineering from Islamic Azad University, Bandar Abbas, Iran, in 2020. She is currently pursuing the Ph.D. degree in electrical engineering with Islamic Azad University, Kashan, Iran. She has also been the Head of the Electrical Engineering Department for two years. She has a five-years' experience in teaching. Her research interests include multi-carrier microgrid, microgrid planning, and blockchain.

**FARHAD SHAHNIA** received the Ph.D. degree in electrical engineering from the Queensland University of Technology, Brisbane, QLD, Australia, in 2012. He is currently an Associate Professor with Murdoch University, Perth, Australia. He has published over 100 articles in the application and control of power electronic converters in distribution systems and microgrids.