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Research Article

Multiobjective Stochastic Power System Expansion Planning Considering Wind Farms and Demand Response

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In recent years, due to the increase in electricity consumption and environmental problems, power system expansion planning requires new technologies. In this regard, the incorporation of renewable energy sources (RESs) and utilization of demand response (DR) programs need disruptive variations in the present power system configurations. This paper proposes a mixed-integer linear robust multiobjective model for generation and transmission expansion planning (GEP-TEP) taking into account wind farms (WFs) and a DR program based on time-of-use pricing. The suggested model is presented via mixed-integer nonlinear programming (MINLP) at the first stage and then transformed into mixed-integer linear programming (MILP) using the Big M linearization technique. Moreover, long- and short-term uncertainties of load demand and WFs are incorporated into the recommended model to achieve more accurate results. The interval-based method is applied for taking into account long-term uncertainties while the scenario-based stochastic model is applied for modeling short-term uncertainties in the recommended GEP–TEP model. Lastly, the suggested model is investigated on various standard test systems to evaluate the effectiveness of the GEP-TEP model.

1. Introduction

Coordinated generation and transmission expansion planning (GEP-TEP) plays a key role in response to the load growth in the future power system. The use of this approach can couple the GEP-TEP problem and simplify the integration of renewable energy sources (RESs) into the power system. In addition, various demand response (DR) programs can also be incorporated into the GEP-TEP problem. However, solving such type of nonlinear optimization problem is computationally complex, and reaching the global optimal solution cannot be ensured. Another complexity with this optimization problem is the random behavior of some parameters such as load demand and RESs. These uncertainties in the problem formulation provide inaccurate results for the planning. Consequently, it is required to propose an appropriate model for the coordinated GEP-TEP problem to obtain an optimal, simple, and robust solution.

So far, many papers are published to address the GEP-TEP problem either by the AC [1–3] or DC power flow equations [4]. The AC power flow provides a nonlinear model; therefore, it is not easy to deal with such complicated equations, especially in a large-scale power system. To prevent such complicated equations and to cope with the nonlinearity of the GEP-TEP problems, DC models are applied [5]. The GEP-TEP model can be based on a multi or single objective. Even though multiobjective GEP-TEP can provide many advantages for power system planning, the method employed to solve this type of optimization is very complex. In [6], a bilevel GEP-TEP model based on game theory is proposed. In this study, the upper level deals with the TEP while the lower level addresses the GEP in a deregulated power system. In [7], a three-level GEP-TEP problem is proposed. In [8], a new model is recommended to eliminate seismic risk. In [9], the GEP-TEP problem is considered with storage systems to provide more flexibility. Some review papers have been also published in these areas in [10–12]. Nevertheless, in the above-mentioned works, the GEP-TEP problem is addressed without considering uncertainties.

A few papers are presented to address power system planning considering uncertainties. In [13], a multistage stochastic MILP formulation is applied to optimize the GEP problem. Similarly, a multistage linear model to cope with uncertainties is proposed in [14]. A stochastic adaptive robust optimization technique for the GEP-TEP problem is suggested in [15]. To minimize the cost and environmental pollution, a robust multiobjective GEP-TEP problem is proposed in [16]. In [17], using the linear formulation, uncertainties in the GEP-TEP are solved. The TEP problem with optimal transmission switching in wind farms (WFs) considering the uncertain parameters is recommended in [18]. The stochastic bilevel model of the TEP problem is also assessed in [19, 20], to model the random behavior of the uncertain parameters.

To cope with the limitations of the above-mentioned papers, this paper proposes a GEP-TEP problem formulation that efficiently coordinates the investment in generation and transmission. It also considers DR as a way to increase the flexibility of the wind-integrated power system. The aim of the model is to reduce the combined cost of generation expansion, transmission expansion, operation, and fuel, while satisfying the uncertainties and constraints of both expansion and operation, and achieving the adequacy and flexibility goals.

Moreover, most of the previous methods for solving the multiobjective GEP-TEP problem are complicated, they suffer from a high computational burden, and the global optimal solution cannot be ensured. Furthermore, the multiobjective GEP-TEP problem taking into account long- and short-term uncertainties and DR at the same time is not investigated in previous works. The Lp-metric method is a powerful tool to address multiobjective problems [21]. The interval-based robust approach has not been used along with the Lp-metric method to deal with the GEP-TEP problem in the literature. Furthermore, the conventional models have not considered the fuel constraints, gaseous emission, and load shedding at the same time. Moreover, the previous models have not simultaneously considered the flexible coordinated GEP-TEP problem with time-of-use DR (TOUDR) programs under long- and short-term uncertainties. The main contributions of this study are listed as follows:

(i) A multiobjective-coordinated GEP-TEP model with integrating WFs and considering the TOUDR program under long- and short-term uncertainties is recommended and solved via the Lp-metric method

(ii) The interval-based method is proposed for modeling long-term uncertainties in the GEP-TEP problem including the peak of load demand and the installed capacity of WFs on the horizon year

(iii) A stochastic approach is suggested for modeling short-term uncertainties in the GEP-TEP problem including daily loads and WF generations

The rest of the paper is prepared as follows: the multiobjective optimization using the LP-metric method is presented in Section 2. The mathematical formulation is developed in Section 3. Section 4 presents the methodology. Section 5 presents case studies and simulations. The conclusion is presented in Section 6.

2. Multiobjective Optimization Using LP-Metric Method

2.1. Multiobjective Optimization. Equation (1) indicates a basic form of the multiobjective problem as

$$\mathrm{Min}[z_1(x), z_2(x), \cdots z_\pi(x)]. \tag{1}$$

The objective functions shown in (1) are typically inconsistent with each other. Enhancing one objective function can ruin the others. The notion of optimality changes into the Pareto optimality in multiobjective problems. The Pareto solution cannot control all of the objective functions [22].

2.2. LP-Metric Method. The LP-metric method is a multiobjective optimization technique that combines different objectives into a single dimensionless objective by using a weighted distance measure. Some of the benefits of the LP-metric method over the simple weighting method are [21] as follows:

(i) It can handle nonconvex objective spaces, while the simple weighting method can only find Pareto-optimal solutions in convex regions

(ii) It can find solutions that are compatible with the decision maker's preferences, while the simple weighting method requires the user to specify the weights in proportion to the relative importance of the objectives

(iii) It can avoid the issue of scaling of the objectives, while the simple weighting method can be sensitive to the units and ranges of the objectives

The considered problem in this study is formulated as multiobjective mixed-integer linear programming (MOMILP). The LP-metric approach as a well-known multicriteria decision-making (MCDM) is used to solve the MOMILP model. In this method, the multiobjective function is divided into two parts, where each part corresponds to one of the objective functions. In each part, the normalized value of each objective function is multiplied by its own weight factor. In this regard, the multiobjective problem is resolved by taking into account each objective function distinctly, and then, a single objective is reformulated. It targets to minimize the summation of the normalized variation between each objective and the optimal values of them. In the suggested model, it is assumed that z_1 and z_2 are two objective functions. According to the LP-metric scheme, MOMILP must be addressed by each one of these two objectives, distinctly. The optimal values for such two objective functions include z_1^* and z_2^*. The LP-metric objective function can be given as [21]

$$z_3 = (\Upsilon)\frac{z_1^* - z_1}{z_1^*} + (1 - \Upsilon)\frac{z_2^* - z_2}{z_2^*}, \tag{2}$$

where $0 \le \Upsilon \le 1$ is given by the planner. By means of the LP-metric taking into account function and considering MOMILP model constraints, the problem becomes a single objective mixed-integer linear programming (SOMILP) model, which can be powerfully handled by the MILP solvers.

3. Mathematical Formulation

3.1. Deterministic GEP-TEP Model. In this part, the deterministic GEP-TEP model is presented and in which the peak load and WFs are considered without uncertainty. Equation (3) is the objective function consisting of four terms. The first term is the GEP cost, including new conventional and WFs. The second term is the cost of installing new transmission lines. The fuel cost of existing and new conventional units is given in the third term. The fourth term is the operation cost, which is obtained by the total energy generated via conventional and WFs.

$$\text{Min } z^{\text{deterministic}} = \sum_t \left\{ \frac{\left\{ \underbrace{\sum_m \sum_i \sum_y \text{Pr}_{m,y}^{\text{cg}} \times \left(\text{ug}_{i,m,y,t} - \text{ug}_{i,m,y,t-1}\right) + \sum_i \sum_y \text{Pr}_y^{\text{wg}} \times \left(\text{uw}_{i,y,t} - \text{uw}_{i,y,t-1}\right)}_{\text{Generation expansion planning cost}} + \underbrace{\sum_i \sum_j \sum_{\text{type}} \sum_{\text{tc}} \text{Pr}_{\text{tc,type}}^{\text{tl}} \times D_{i,j} \times \left(\text{ut}_{i,j,\text{tc},\text{type},t} - \text{ut}_{i,j,\text{tc},\text{type},t-1}\right)}_{\text{Transmission expansion planning cost}} + \underbrace{\sum_f \sum_i \sum_m \text{FT}_{f,i,m,t} \times \left(\text{Pr}_f^{\text{fuel1}} + \text{Pr}_f^{\text{fuel2}} \times D_{f,i}\right)}_{\text{Fuel cost}} + \underbrace{\sum_i \sum_m \alpha_m \times \left(\text{En}_{i,m,t}^{\text{cg}} + \text{En}_{i,t}^{\text{wg}}\right)}_{\text{Operation cost}} \right\}}{(1+d)^t} \right\}, \tag{3}$$

S.t:

$$\sum_y \sum_m P_{i,m,y,t}^{\text{cg}} + \sum_y P_{i,y,t}^{\text{wg}} - \text{load}_{i,t} + P_{i,t}^{\text{shed}} = \sum_j P_{i,j,t}^{\text{flow}}, \tag{4}$$

$$\sum_i \sum_y \sum_m P_{i,m,y,k,t}^{\text{cg}} + \sum_i \sum_y P_{i,y,k,t}^{\text{wg}} - \sum_i \text{load}_{i,t} + \sum_i P_{i,k,t}^{\text{shed}} = 0, \tag{5}$$

$$\sum_i \text{load}_{i,t} \times \text{HS}_i \le \sum_i \sum_m \left(\text{En}_{i,m,t}^{\text{cg}} + \text{En}_{i,t}^{\text{wg}}\right), \tag{6}$$

$$\begin{aligned} \eta_m \times \text{MHO}_m \times \left(\Delta P_{i,m,y,t}^{\text{cg}} + \Delta P_{i,y,t}^{\text{wg}}\right) \\ \le \left(\text{En}_{i,m,t}^{\text{cg}} + \text{En}_{i,t}^{\text{wg}}\right) \le \text{MHO}_m \times \left(\Delta P_{i,m,y,t}^{\text{cg}} + \Delta P_{i,y,t}^{\text{wg}}\right), \end{aligned} \tag{7}$$

$$P_{i,t}^{\text{shed}} \le \text{load}_{i,t}, \tag{8}$$

$$\sum_i P_{i,t}^{\text{shed}} \le P_t^{\text{shed.max}}, \tag{9}$$

$$P_{i,m,y,t}^{\text{cg}} \le P_{i,m,y,t}^{\text{cg.plan}}, \tag{10}$$

$$P_{i,y,k,t}^{\text{wg}} \le P_{i,y,t}^{\text{wg.plan}}, \tag{11}$$

$$p^{\text{wg.plan.min}} \le \sum_t \sum_i \sum_y P_{i,y,t}^{\text{wg.plan}}, \tag{12}$$

$$P_{i,m,y,t}^{\text{cg.plan}} - P_{i,m,y}^{\text{cg.ini}} = \text{ug}_{i,m,y,t} \times P_{m,y}^{\text{cg.can}}, \tag{13}$$

$$P_{i,y,t}^{\text{wg.plan}} - P_{i,y}^{\text{wg.ini}} = \text{uw}_{i,m,y,t} \times P_y^{\text{wg.cand}}, \tag{14}$$

$$-P_{i,j}^{\text{transmission}} \le P_{i,j}^{\text{ini,flow}} \le P_{i,j}^{\text{transmission}}, \tag{15}$$

$$-\left(P_{i,j}^{\text{trans}} + \Delta P_{i,j,t}^{\text{trans}}\right) \le P_{i,j,t}^{\text{flow}} \le P_{i,j}^{\text{trans}} + \Delta P_{i,j,t}^{\text{trans}}, \tag{16}$$

$$P_{i,j}^{\text{ini,flow}} = B_{i,j}^{\text{ini}} \times \left(\theta_i^{\text{ini}} - \theta_j^{\text{ini}}\right), \tag{17}$$

$$P_{i,j,k,t}^{\text{flow}} = B_{i,j,t}^{\text{plan}} \times \left(\theta_{i,t}^{\text{plan}} - \theta_{j,t}^{\text{plan}}\right), \tag{18}$$

$$\theta^{\min} \le \theta_{i,t}^{\text{plan}} \le \theta^{\max}, \tag{19}$$

$$\begin{aligned} -\left(P_{i,j}^{\text{trans}} + \Delta P_{i,j,t}^{\text{trans}}\right) &\le \left(B_{i,j}^{\text{ini}} + \Delta B_{i,j,t}\right) \\ &\times \left(\theta_i^{\text{ini}} + \Delta\theta_{i,t} - \theta_j^{\text{ini}} - \Delta\theta_{j,t}\right) \\ &\le P_{i,j}^{\text{trans}} + \Delta P_{i,j,t}^{\text{trans}} - P_{i,j}^{\text{transmisson}} \\ &\le B_{i,j}^{\text{ini}} \times \left(\theta_i^{\text{ini}} - \theta_j^{\text{ini}}\right) \le P_{i,j}^{\text{transmisson}}, \end{aligned} \tag{20}$$

$$\begin{aligned} \Big| B_{i,j}^{\text{ini}} \times \left(\Delta\theta_{i,k,t} - \Delta\theta_{j,k,t}\right) + \Delta B_{i,j,t} \times \left(\theta_i^{\text{ini}} - \theta_j^{\text{ini}}\right) + \Delta B_{i,j,t} \\ \times \left(\Delta\theta_{i,k,t} - \Delta\theta_{j,k,t}\right) \Big| \le \Delta P_{i,j}^{\text{trans}}, \end{aligned} \tag{21}$$

$$\Delta P_{i,j,t}^{\text{trans}} = \sum_{\text{tc}} \sum_{\text{type}} \text{ut}_{i,j,\text{tc},\text{type},t} \times P_{\text{tc,type}}^{\text{can}}, \tag{22}$$

$$\Delta B_{i,j,t} = B_{i,j,t}^{\text{plan}} - B_{i,j}^{\text{initial}} = \sum_{\text{tc}} \sum_{\text{type}} \text{ut}_{i,j,tc,\text{type},t} \times B_{\text{tc,type}}^{\text{can}}, \tag{23}$$

$$\sum_i \sum_m \gamma_m \times \text{En}_{i,m,t}^{\text{cg}} \le \text{GE}_t^{\max}, \tag{24}$$

$$\sum_m \text{FT}_{f,i,m,t} = \psi_m \times \text{En}_{i,m,t}^{\text{cg}}, \tag{25}$$

$$\sum_i \sum_m \text{FT}_{f,i,m,t} \le \text{FS}_f^{\max}, \tag{26}$$

$$\text{FT}_{f,i,m,t} \le \text{FTL}_{f,i}^{\max}. \tag{27}$$

The power balance equation is presented in (4). The total power generation equality by power consumption is indicated in (5). Equation (6) ensures that the generated energy by the system must be more than the required energy demand. The energy generated by new power plants is based on the yearly maximum hours of their operation and contribution factor as can be seen in (7). The load shedding cannot be higher than the load as forced by (8). Equation (9) indicates that the total annual load shedding should be smaller than the maximum allowable amount per year. The power generated by conventional and WFs should be lower than the planned amount as presented in (10) and (11), respectively. The installed WFs must be greater than the minimum amount in the 5-year horizon as forced by (12).

Equations (13) and (14) decide on the installation of conventional and WFs, respectively. Equations (15) and (16) impose the restriction on transmission power flow capacity before and after planning, while these values are obtained from equations (17) and (18), respectively. Upper and lower limits in voltage angle are applied by (19). Equations (20) and (21) can be achieved by replacing (17) and (18) in (15) and (16). It is notable that (21) is nonlinear because of the multiplication of two decision variables comprising ΔB and $\Delta\theta$. The Big M linearization scheme [23] is used to tackle the nonlinearity of (21) (see [23] for details). The change in transmission power flow and susceptance matrix can be calculated by (22) and (23), respectively. The gaseous emission of conventional units is limited by (24). The fuel consumption of conventional units is calculated by (25) and limited by imposing (26) and (27).

3.2. Scenario-Based Modeling and TOUDR Program. Considering uncertainties in the planning model to obtain more accurate results is required. The random behavior of WFs' generation and daily loads necessitates considering short-term uncertainties. On the other hand, considering the DR program along with these uncertainties can greatly neutralize the destructive effects of uncertainty parameters. Here, the scenario-based method has been employed to consider the daily uncertainties in the production of WFs and electrical load as short-term uncertainties. Scenarios present operation circumstances in each hour of the horizon year. Consequently, a scenario with the probability of occurrence has been created for each hour of the target year, which has been reduced using the K-mean algorithm to 48 operational scenarios [24]. As a result, a number of constraints related to the production of WFs and electrical load should be changed, while the most important of them are as follows:

$$\begin{aligned}
&\sum_y\sum_m p^{\mathrm{cg}}_{i,m,y,t,w} + \sum_y k^{\mathrm{wg}}_w \times p^{\mathrm{wg}}_{i,y,t} - \left(k^l_w \times \mathrm{Load}_{i,t}\right) + p^{\mathrm{shed}}_{i,t,w} = \sum_j p^{\mathrm{flow}}_{i,j,t,w},\\
&\sum_i\sum_y\sum_m p^{\mathrm{cg}}_{i,m,y,t,w} - \sum_i k^l_w \times \mathrm{Load}_{i,t} + \sum_i\sum_y k^{\mathrm{wg}}_w \times p^{\mathrm{wg}}_{i,y,t,w} + \sum_i P^{\mathrm{shed}}_{i,t,w} = 0,\\
&\sum_i\sum_w \beta_w \times k^l_w \times \mathrm{Load}_{i,t} \le \sum_i\sum_m \left(\mathrm{En}^{\mathrm{cg}}_{i,m,t,w} + \mathrm{En}^{\mathrm{wg}}_{i,t,w}\right),\\
&P^{\mathrm{shed}}_{i,t,w} \le k^l_w \times \mathrm{Load}_{i,t},\\
&\sum_i\sum_w p^{\mathrm{shed}}_{i,t,w} \le P^{\mathrm{shed.max}}_t.
\end{aligned} \tag{28}$$

Since various uncertainties in this model are considered, a stepwise approximation-based TOUDR scheme is used in this paper. Five peak load rates are expected here. The predictable demand after using the TOUDR is given in (29). It is assumed that only one peak load rate is active as guaranteed by (30). Furthermore, customer demand cannot be adversely affected by the TOUDR as (31).

It is well-known that the DR program is based on peak load demand and electricity price and can be implemented in different schemes such as TOUDR. Since the peak load and, also, energy price are forecastable in the future with acceptable accuracy, the DR is also predictable. In addition, the elasticity for different types of load in any country is known [25].

$$\mathrm{Load}^{\mathrm{TOUDR}}_{i,t,w} = k^l_w \times \mathrm{Load}_{i,t} \sum_{\mathrm{plr}} \mathrm{ud}_{i,t,w,\mathrm{plr}} \times \mathrm{drr}_{\mathrm{plr}}, \tag{29}$$

$$\sum_{\mathrm{plr}} \mathrm{ud}_{i,t,w,\mathrm{plr}} \le 1, \tag{30}$$

$$\sum_w k^l_w \times \mathrm{Load}_{i,t} \le \sum_w\sum_{\mathrm{plr}} k^l_w \mathrm{Load}_{i,t} \times \mathrm{ud}_{i,t,w,\mathrm{plr}} \times \mathrm{drr}_{\mathrm{plr}}. \tag{31}$$

3.3. Multiobjective Model Using Interval-Based Optimization. In the previous section, short-term uncertainties in daily load and WF productions were modeled by the scenario-based method. There are different methods and tools that can be used to account for the stochastic nature of load demand in the long-term horizon. One of the most efficient methods for considering this uncertainty is the robust method. This is a decision-making technique that considers the worst-case scenarios of uncertainties and provides solutions that are immune to deviations from the expected values. It can handle nonconvex and complex problems and provide rigorous guarantees on the future operation risk of planning [26].

An interval-based model together with the LP-metric technique is offered here to integrate the long-term uncertainties in the GEP-TEP model. The interval-based GEP-TEP model is defined as follows:

$$\min z(x), \tag{32}$$

$$f_n(x) \le 0, \tag{33}$$

$$g_k(x) \le \left[b^{\mathrm{lo}}_k, b^{\mathrm{up}}_k\right], \tag{34}$$

$$h_n(x) = \left[d^{\mathrm{lo}}_n, d^{\mathrm{up}}_n\right], \tag{35}$$

where x is decision variables and (32) denotes the objective function (3). Equation (33) indicates deterministic constraints. Equations (34) and (35) are interval-based inequalities and equalities constraints, respectively. Here, there is no inequality constraint, (4)–(6) and (8) are interval-based equality constraints, and the rest of the constraints are deterministic. In addition, $[d^{\mathrm{lo}}_n, d^{\mathrm{up}}_n]$ indicates the interval forms of $[\mathrm{Load}^{\mathrm{lo}}_{i,t}, \mathrm{Load}^{\mathrm{up}}_{i,t}]$ and $P^{\mathrm{wg.lo}}_{i,y,t}, P^{\mathrm{wg.up}}_{i,y,t}$. The equality (equations (4)–(6) and (8)) can be replaced by (36)–(39), respectively.

$$\sum_y \sum_m P^{cg}_{i,m,y,t} + \sum_y k^{wg}_w \times \left[P^{wg.lo}_{i,y,t}, P^{wg.up}_{i,y,t}\right] - \left[\text{Load}^{TOUDR.lo}_{i,t,w}, \text{Load}^{TOUDR.up}_{i,t,w}\right] + P^{shed}_{i,t} = \sum_j P^{flow}_{i,j,t}, \quad (36)$$

$$\sum_i \sum_y \sum_m P^{cg}_{i,m,y,k,t} + \sum_i \sum_y k^{wg}_w \times \left[P^{wg.lo}_{i,y,t}, P^{wg.up}_{i,y,t}\right] - \sum_i \left[\text{Load}^{TOUDR.lo}_{i,t,w}, \text{Load}^{TOUDR.up}_{i,t,w}\right] + \sum_i P^{shed}_{i,k,t} = 0, \quad (37)$$

$$\sum_i \sum_w \left[\text{Load}^{TOUDR.lo}_{i,t,w}, \text{Load}^{TOUDR.up}_{i,t,w}\right] \le \sum_i \sum_m \left(\text{En}^{cg}_{i,m,t} + \text{En}^{wg}_{i,t}\right), \quad (38)$$

$$P^{shed}_{i,t} \le \left[\text{Load}^{TOUDR.lo}_{i,t,w}, \text{Load}^{TOUDR.up}_{i,t,w}\right]. \quad (39)$$

3.3.1. The Probability Degree Definition and Transferring Model. In this paper, the probability degree (λ) is employed to transfer the interval-based constraints into deterministic ones. In interval mathematics, the comparison of the two intervals is to determine which one is better than the other. For this reason, the probability degree is used to describe the degree to which interval is better than another interval. More details are given in [27]. An example is provided here for the better understanding of the difference between an interval and a real number. Assuming that "a" is a real number and $[B = b^{lo}, b^{up}]$ is an interval, "a" can be located in three positions as displayed in Figure 1, and the related probability degree can be given as

$$P(a \le B) = \begin{cases} 1, a \le b^{lo} \\ \dfrac{b^{up} - a}{b^{up} - b^{lo}}, \underline{z} < a \le b^{up} \\ 0, a > b^{up} \end{cases}. \quad (40)$$

In (40), the variable in the interval tracks a uniform distribution, and $P\,(a \le B)$ donates the probability degree for $a \le B$. The value of the probability degree is changing based on the level of risk where $\lambda \in [0\,;1]$. When $a \le B$ in (39), $P\,(a \le B) \ge \lambda$ can be obtained as follows:

$$a \le b^{lo}\lambda + b^{up}(1 - \lambda). \quad (41)$$

Based on the description of probability degree, λ is the level of risk to address uncertainties. If the λ is close to zero in equation (41), the interval-based inequality approaches to b^{up}, which is optimistic for WFs and extremely pessimistic for electrical load. Also, if the λ is close to one, the interval-based inequality approaches to b^{lo} and has a tendency to minimize the uncertainties of the interval $[b^{lo}, b^{up}]$, which is extremely pessimistic for WFs and extremely optimistic for electrical load. Consequently, the higher value of λ specifies the tighter bound of the uncertainties and vice versa. Using (41), the equation of the interval-based model changes to deterministic ones as follows:

$$h_n(x) = d^{lo}_n \lambda_{h,n} + d^{up}_n (1 - \lambda_{h,n}). \quad (42)$$

So (36)–(39) can be transformed to

$$\sum_y \sum_m P^{cg}_{i,m,y,t} + \sum_y k^{wg}_w \times \left[P^{wg.lo}_{i,y,t} \times \lambda^{wg} +, P^{wg.up}_{i,y,t}(1 - \lambda^{wg})\right] - \left[\text{Load}^{TOUDR.lo}_{i,t,w} \times \lambda^l + \text{Load}^{TOUDR.up}_{i,t,w}\left(1 - \lambda^l\right)\right] + P^{shed}_{i,t} = \sum_j P^{flow}_{i,j,t}, \quad (43)$$

$$\sum_i \sum_y \sum_m P^{cg}_{i,m,y,k,t} + \sum_i \sum_y k^{wg}_w \times \left[P^{wg.lo}_{i,y,t} \times \lambda^{wg} +, P^{wg.up}_{i,y,t}(1 - \lambda^{wg})\right] - \sum_i \left[\text{Load}^{TOUDR.lo}_{i,t,w} \times \lambda^l + \text{Load}^{TOUDR.up}_{i,t,w}\left(1 - \lambda^l\right)\right] + \sum_i P^{shed}_{i,k,t} = 0, \quad (44)$$

$$\sum_i \left[\text{Load}^{TOUDR.lo}_{i,t,w} \times \lambda^l + \text{Load}^{TOUDR.up}_{i,t,w}\left(1 - \lambda^l\right)\right] \times \le \sum_i \sum_m \left(\text{En}^{cg}_{i,m,t} + \text{En}^{wg}_{i,t}\right), \quad (45)$$

$$P^{shed}_{i,t} \le \left[\text{Load}^{TOUDR.lo}_{i,t,w} \times \lambda^l + \text{Load}^{TOUDR.up}_{i,t,w}\left(1 - \lambda^l\right)\right]. \quad (46)$$

To cope with the robust multiobjective model, first, the deterministic model must be addressed, and the total cost in the stochastic case should be attained. Next, an upper bound on the total expansion cost is set based on the stochastic cost. In (43)–(46), the forecasted peak of electrical load and the peak of WF installation are allowed to change by λ. Moreover, an extra constraint must be set to the total cost, to make the model economically operational while maximizing its robustness as indicated in (47).

$$z^{Robust} \le (1 + U) z^{stochastic}. \quad (47)$$

Now, the problem should be solved to minimizing λ^l and maximizing λ^{wg} by LP-metric method as follows:

$$z = (\Upsilon) \frac{\lambda^{l.*} - \lambda^l}{\lambda^{l.*}} - (1 - \Upsilon) \frac{\lambda^{wg.*} - \lambda^{wg}}{\lambda^{wg.*}}. \quad (48)$$

It is noteworthy that the multiplication of two decision variables including λ^{wg} and $P^{wg}_{i,y,t}$ in (43), and (44), makes the model nonlinear.

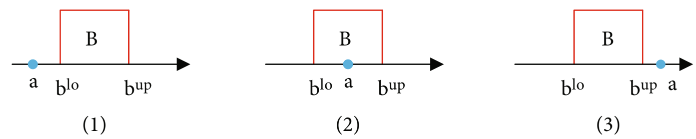

Figure 1: Relation between a real number and an interval [27].

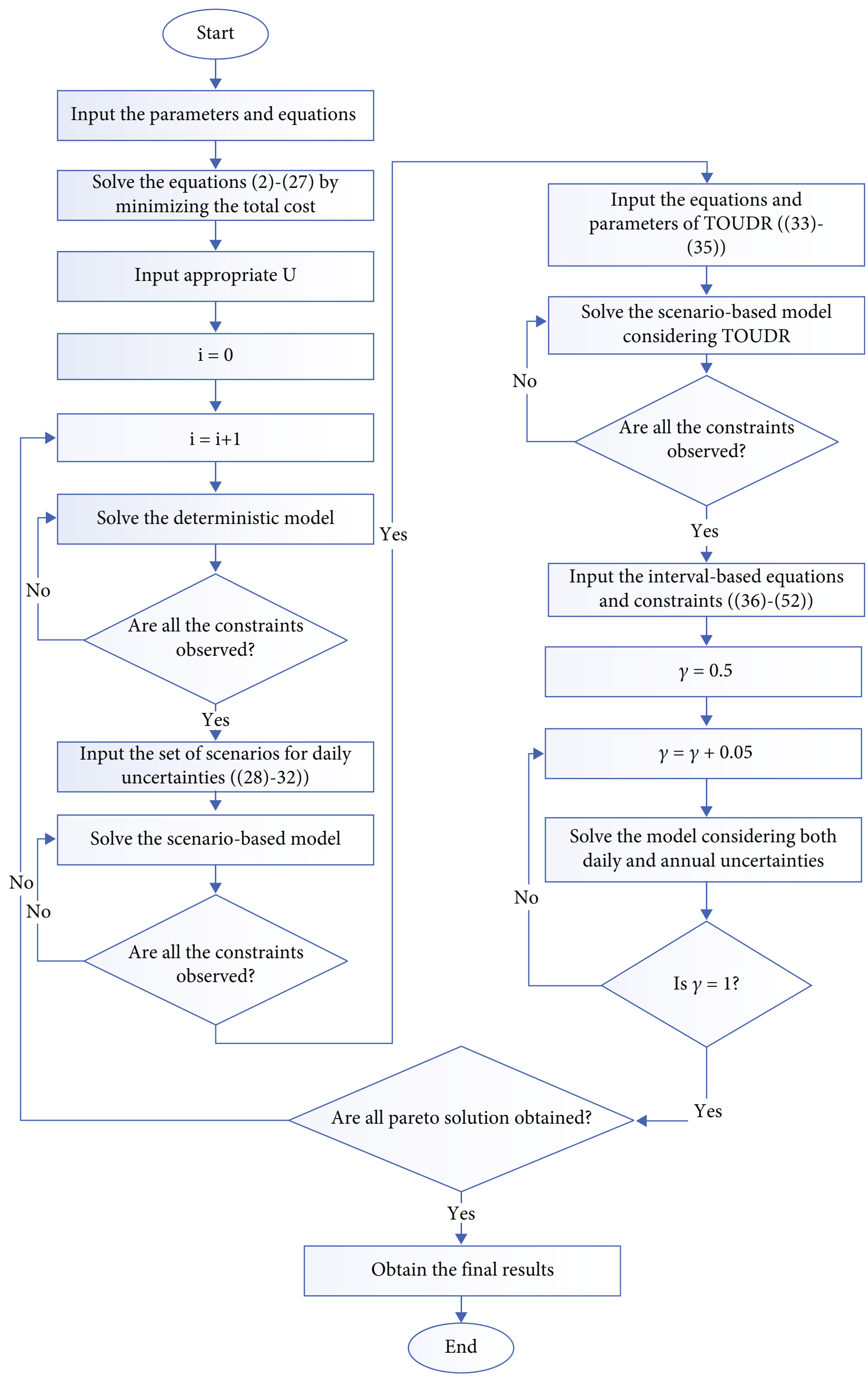

Figure 2: Flowchart of the suggested technique.

Table 1: Candidate generation units and transmission lines.

Technology	Generation units 1		2		3		Candidate lines	1		2	
	Capacity (MW)	Cost (∃/MW)	Capacity (MW)	Cost (∃/MW)	Capacity (MW)	Cost (∃/MW)	Capacity (MW)	Susceptance (pu)	Cost (∃/MW)	Susceptance	Cost (∃/MW)
WFs	15	19.5	20	26	50	65	50	0.128	144.39	0.192	129.95
Hydro	50	62.5	60	70	70	82.6	80	0.192	151.17	0.224	136.05
Steam	75	75	100	95	125	112.5	100	0.224	155.69	0.336	140.12
Gas	30	27	40	34	50	40	150	0.392	163.49	0.420	147.14
Combined	135	148.5	160	168	180	180	180	0.420	220.26	0.490	198.23

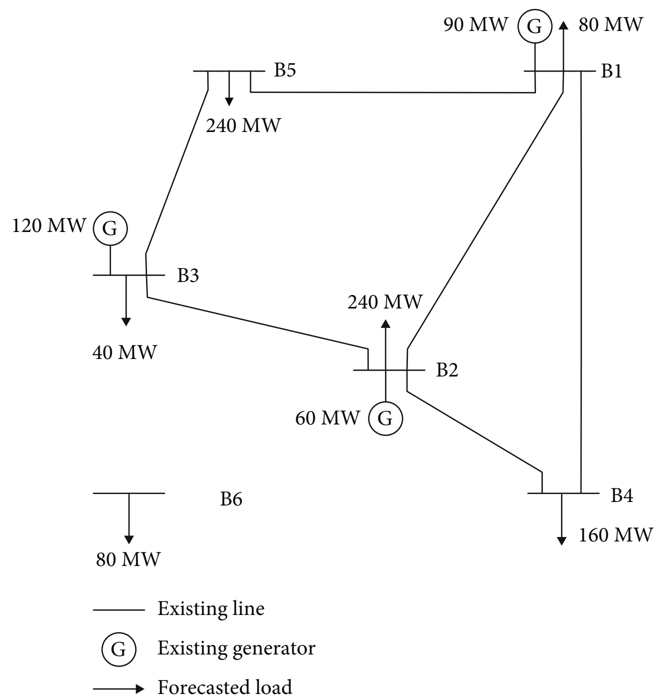

Figure 3: The Garver system in preexpansion state.

4. Solution Methodology

The robust interval- and scenario-based approaches have been used to take into account long- and short-term uncertainties, respectively. The model allows the planner to select the appropriate planning considering uncertainties and demand response. The optimal planning steps are as follows:

(i) Input the equations and parameters

(ii) The Big M linearization is applied to handle nonlinearities

(iii) The GEP-TEP problem is solved via the deterministic methodology

(iv) The model is improved based on scenario-based stochastic to deal with daily uncertainties in electrical load and the power produced by WFs as presented in Section 3.2

Table 2: Installed elements in the deterministic approach.

Year	Added elements
$t = 1$	65 MW WF at bus 5 60 MW hydro unit at bus 6 20 MW WF at bus 6 50 MW transmission line between buses 2 and 6
$t = 2$	—
$t = 3$	30 MW gas unit at bus 5
$t = 4$	50 MW gas unit at bus 2 50 MW gas unit at bus 4 90 MW gas unit at bus 5
$t = 5$	60 MW gas unit at bus 1 60 MW gas unit at bus 2 60 MW gas unit at bus 4 60 MW gas unit at bus 5

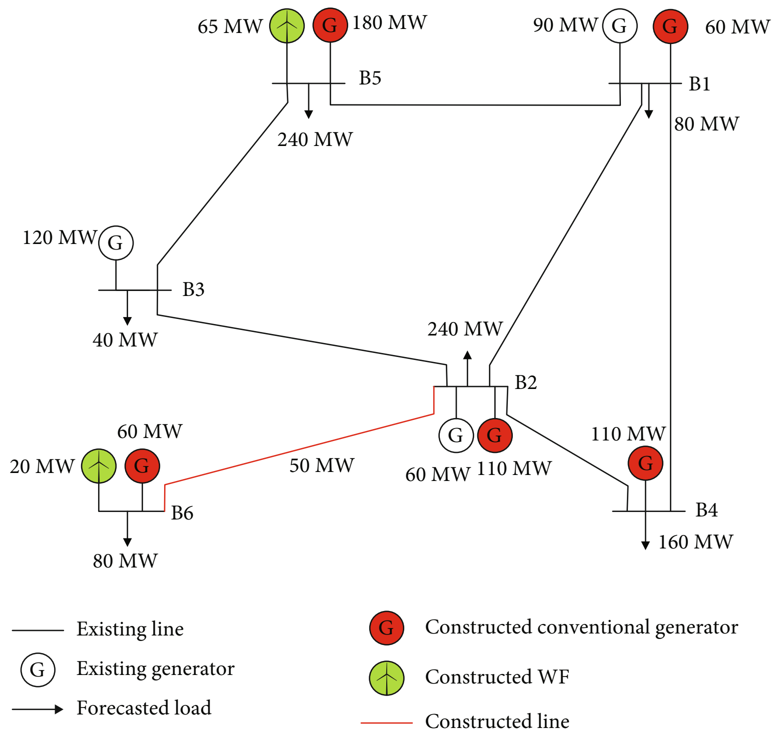

FIGURE 4: The Garver system in the deterministic approach.

(v) At this stage, the TOUDR is added to the previous stage

(vi) The model is altered to an interval- and scenario-based by means of the method given in Section 3.3

(vii) The model is solved using MOMILP to obtain the robust region for load and WF installation at the same time

(viii) Step (vii) is repeated for different values of Υ

To better expose the procedure of the solution method, the flowchart is depicted in Figure 2.

5. Numerical Simulations

In this part, various numerical results are provided through the CPLEX solver in the GAMS optimization package on 6-bus Garver [28] and 24-bus IEEE test systems [29]. The simulations have a threefold purpose: (i) to validate the proposed MILP-based GEP-TEP deterministic model; (ii) to investigate the effects of short-term uncertainties including WFs' generation and daily loads using the scenario-based stochastic approach along with considering the TOUDR in the dynamic GEP-TEP model; (iii) the analysis of increasing investment cost on the long-term uncertainties of WF installation capacity and load demand by applying a multiobjective robust GEP-TEP model. The information of candidate generation units and transmission lines are given in Table 1. The resulting optimization problem has been run on an Intel® CoreTM i7, 12.00 GB RAM personal computer and solved over 5-year horizon.

TABLE 3: Installed elements in the stochastic scenario-based problem.

Year	Added elements
$t = 1$	15 MW WF at bus 4 40 MW gas unit at bus 5 35 MW WF at bus 5 70 MW hydro unit at bus 6 50 MW transmission line between buses 4 and 6
$t = 2$	—
$t = 3$	60 MW gas unit at bus 5
$t = 4$	60 MW gas unit at bus 4 100 MW steam unit at bus 5
$t = 5$	60 MW gas unit at bus 1 60 MW gas unit at bus 2 90 MW gas unit at bus 5

5.1. Garver Test System. The used Garver's 6-bus system is the most well-known test power system for planning studies [28]. In this power system, the existing conventional units include a 90 MW gas unit at bus 1, a 60 MW steam unit at bus 2, and a 120 MW steam unit at bus 3. The preexpansion model of this network is illustrated in Figure 3. It is assumed that there are no water resources required for installation of the hydro unit in 2-5 buses, the minimum total installed WF at the end of the fifth year must be more than 50 MW, it is not possible to install the gas turbine unit in bus 6 due to pollution restrictions, and the load shedding cannot be more

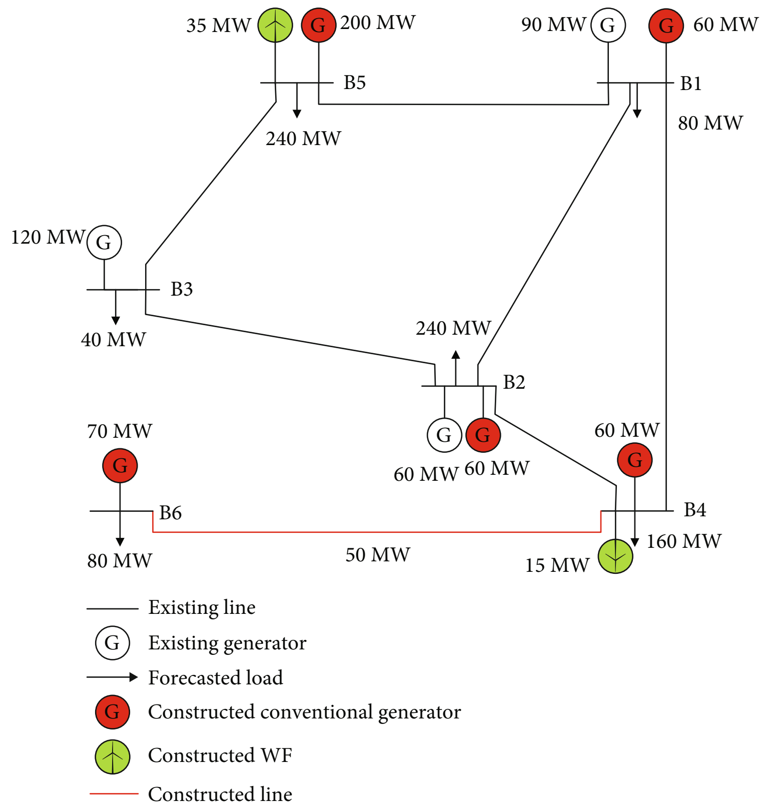

Figure 5: The Garver system in the stochastic scenario-based problem considering short-term uncertainties.

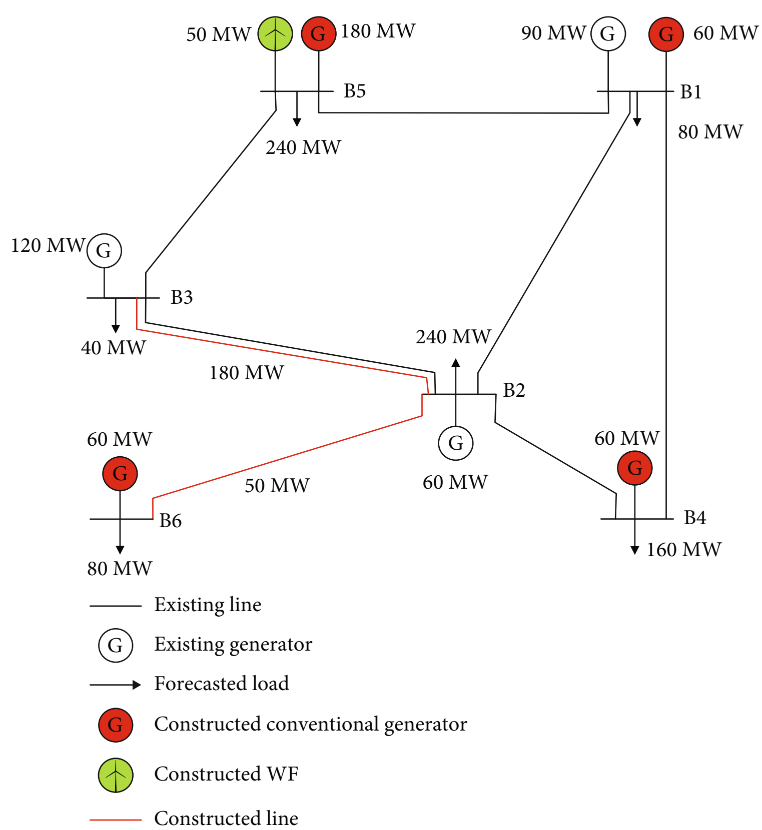

Figure 6: The Garver system in the stochastic scenario-based problem considering short-term uncertainties and TOUDR.

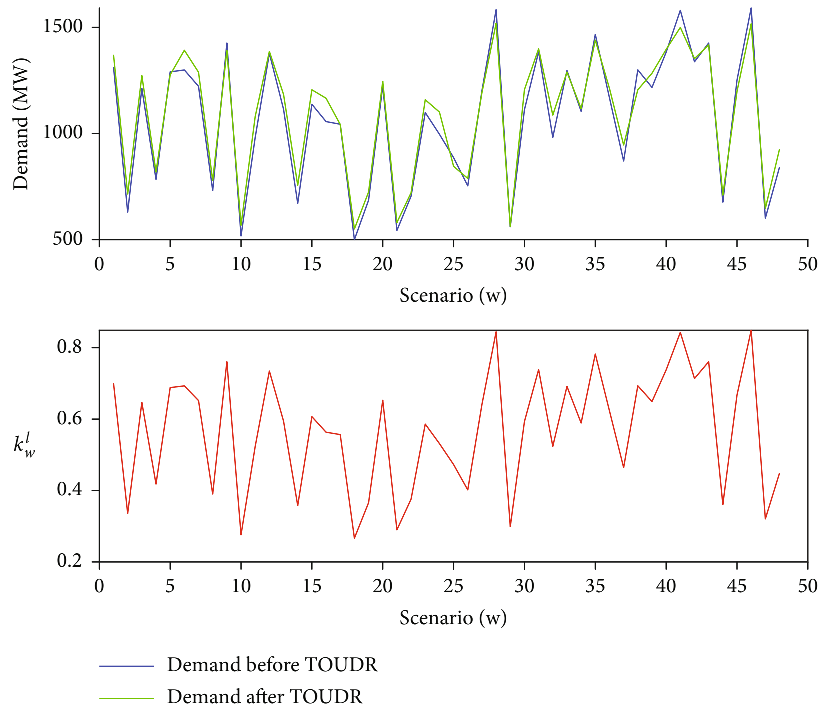

FIGURE 7: Load demand before and after TOUDR in different scenarios.

than 40 MW in each year. In this part, the outcomes are given in four various circumstances, containing the single-objective GEP-TEP problem via the deterministic method, the scenario-based model to deal with short-term uncertainties, the scenario-based approach to cope with short-term uncertainties, and the TOUDR at the same time, and the multiobjective interval-based GEP-TEP is solved via LP-metric to robust long- and short-term uncertainties considering the TOUDR.

5.1.1. Deterministic Results. In this section, the simulations are provided via the peak amount of electrical load and WFs. The total cost of planning is 6.66E6. The added elements in this case study are shown in Table 2. As observed in Table 2, (i) bus 6 is connected to bus 2 by a 50 MW transmission line at the first year of the planning to prevent the islanding of bus 6; (ii) due to the impossibility of installing the gas unit and the existence of water resources in bus 6, a 60 MW hydro unit and 20 MW WF have been installed in this bus; (iii) a total of 85 MW of WFs have been installed by the fifth year to different buses according to the defined constraints (minimum installed WFs). Figure 4 also illustrates the Garver network in this case study.

5.1.2. GEP-TEP with Short-Term Uncertainties. Here, the results of stochastic GEP-TEP with short-term uncertainties including daily load and WFs' generation are obtained. The added element in considered horizon years is shown in Table 3. Since considering daily load scenarios instead of peak load has a large impact on the required power network, the total cost is reduced by 10.5%, which is equal to 5.96E6. On the other hand, considering scenarios for the generation of WFs can reduce their production compared to peak generation. Therefore, the amount of installed WFs has been reduced to 50 MW, which is forced by constrain (12). The Garver network in this case study is depicted in Figure 5. As seen, bus 6 is connected to bus 4 via the 50 MW transmission line.

TABLE 4: Installed elements in the stochastic scenario-based problem considering TOUDR.

Year	Added elements
$t = 1$	40 MW gas unit at bus 5 50 MW WF at bus 5 60 MW hydro unit at bus 6 180 MW transmission line between buses 2 and 3 50 MW transmission line between buses 2 and 6
$t = 2$	—
$t = 3$	30 MW gas unit at bus 5
$t = 4$	60 MW gas unit at bus 4 50 MW gas unit at bus 5
$t = 5$	60 MW gas unit at bus 1 60 MW gas unit at bus 5

5.1.3. GEP-TEP with Short-Term Uncertainties and TOUDR. Here, the effects of short-term uncertainties and the TOUDR program to the GEP-TEP model are examined. As shown in Figure 6, a noticeable change has been made to the added elements to the considered network, which has greatly reduced the total cost. There is a noteworthy positive correlation between using the TOUDR and the total cost, which is equal to 4.62E6. The total cost compared to

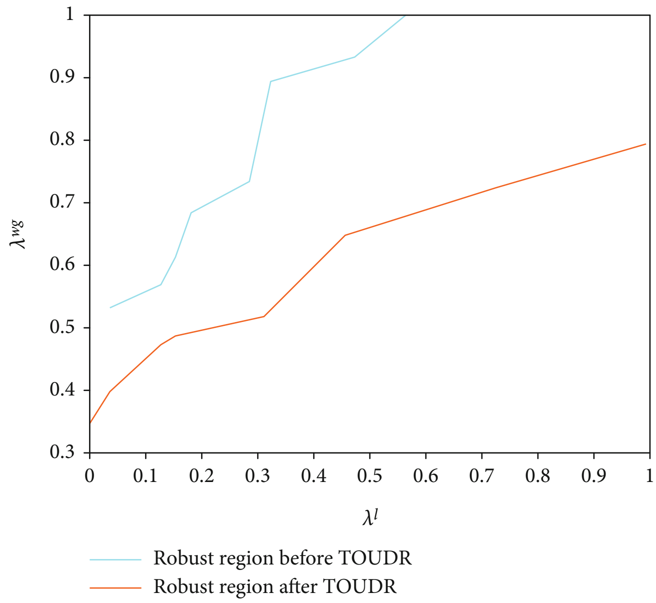

Figure 8: Robust region for λ^l and λ^{wg} before and after TOUDR.

the scenario-based approach without the TOUDR and deterministic approach has decreased by 22.5% and 30.6%, respectively. The electrical demand in different scenarios before and after using the TOUDR is illustrated in Figure 7. It is obvious that when the load increases by the scenario coefficient (k_w^l), its value decreases by the TOUDR coefficient ($\mathrm{drr}_{\mathrm{plr}}$). Also, when the load increases by the scenario coefficient (k_w^l), its value decreases by the TOUDR coefficient ($\mathrm{drr}_{\mathrm{plr}}$). What is interesting is that the total load in all scenarios has been increased after using the TOUDR from $5.1140E+04$ to $5.2535E+04$. The elements added to the considered network are shown in Table 4. One of the most important changes compared to the previous case is the installation of a 180 MW transmission line between bus 2 and bus 3, the biggest reason being the transfer of excess power from bus 3 to bus 2.

5.1.4. Multiobjective GEP-TEP with Long- and Short-Term Uncertainties. Here, the issue is inspected as a multiobjective GEP-TEP model taking into account short-term uncertainties via scenario-based modeling and long-term uncertainties using robust optimization. In this case study, it is assumed ±30% interval width for long-term uncertainties including load demand and WFs' installation. λ^l and λ^{wg} are the probability degrees for uncertain intervals of long-term uncertainties. As mentioned in Section 4, if the λ is near to 1, the uncertain parameter will be near to the lower bound, which is optimistic for the annual peak amount of electrical load and pessimistic for the annual peak amount of WFs' installation. This situation is opposite for λ near to 0. As a result, the model should minimize λ^l and maximize λ^{wg} in a multiobjective robust pessimistic problem. Figure 8 depicts the different values of λ^l and λ^{wg} at $U=0.25$ before and after using the TOUDR. It is assumed that the weighting factor of Υ starts from 0.75 and reaches 1 with the step up of 0.05 because load demand has more effect on the network. As can be seen from Figure 8, the graph is in a better position after applying the TOUDR. It is due to the fact that λ^{wg} has a smaller value when considering the TOUDR while λ^l has a larger value when considering the TOUDR.

Table 5: The results of IEEE 24-bus.

Type of planning	Obtained results
Deterministic approach	205 MW WF Total cost = $2.12E+9$
Scenario-based stochastic	220 MW WFs Total cost = $1.94E+9$
Considering TOUDR	Load before = $4.0495E+5$ Load after = $4.0496E+5$
Robust stochastic	$U=0.25$ $\Upsilon=0.8$ $\lambda^l=0.523$ $\lambda^{wg}=0.702$

5.2. IEEE 24-Bus Test System. Here, the model is investigated on a large test system considering the long- and short-term uncertainties as well as the TOUDR. It is assumed that the minimum installed WF capacity at the end of the fifth year must be more than 200 MW, and the other information is based on the IEEE 24-bus test system given in [12]. The results of different case studies are given in Table 5. As observed, the total cost in the deterministic approach is 2.12E9 considering 205 MW WF installation. By considering the set of scenarios for the short-term uncertainties including daily load and WF generation, the total cost is decreased to 1.94E9. It is reduced by 8.5% compared to the deterministic approach. Moreover, the installed WFs are equal to 220 MW in the fifth year of the horizon. The total cost has been reduced by about 31.5% and is equal to 1.33E9∃ after applying for the TOUDR program. In the multiobjective model taking into account both long- and short-term uncertainties, the probability degree for the annual peak amount of electrical load and WF installation is $\lambda^l = 0.523$ and $\lambda^{wg} = 0.702$, respectively.

To show the effectiveness of the proposed model, a small and a large test network is used for simulation. In both cases, the results of simulations show that considering the TOUDR program leads to a considerable reduction in the total cost and increasing the flexibility of power system in the presence of WFs. Moreover, the robust GEP–TEP problem allows implementing an interval approach on long-term uncertainties to provide high protection risk against long-term decisions, while it is implemented via scenarios for short-term uncertainties since they do not need high-risk protection. The simulation results show that the GEP–TEP problem highly depends on both long- and short-term uncertainties.

6. Conclusion

In this study, a stochastic multiobjective robust method is recommended for the GEP-TEP problem with WFs in a power system considering the TOUDR program. The MINLP original model in this study is converted to the MILP model using linearization approaches to attain a globally optimal solution with low calculation time and error. Then, the MOMILP model is solved using the LP-metric method. Long-term uncertainties including annual peak load and WFs' installation capacity as well as short-term uncertainties containing daily load demand and WFs' generations are incorporated in the GEP-TEP problem. The long-term uncertainties are modeled via the interval-based approach while the short-term uncertainties are addressed by the scenario-based approach. To provide more flexibility for the GEP-TEP problem, the TOUDR is also used. The recommended model is simulated on Garver 6-bus and IEEE 24-bus test systems. Lastly, it is concluded that the suggested model can provide robust, reliable, and flexible power system planning.

Indexes (Sets)

f: Set for fuel sources
I, j: Set for buses
m: Set for conventional generation units
t: Set for the years of the planning horizon
tc: Set for available transmission line capacity
type: Set for available reactance transmission capacity
w: Set for scenarios
y: Set for available capacities for the conventional generation
s: Interval-based inequalities
n: Interval-based equalities
plr: Peak load rate
π: Number of objective functions.

Superscripts

can: Candidate element
ini: Preexpansion element
max: Maximum amount
min: Minimum amount
flow: Power flow between buses
trans: Transmission capacity between buses in preexpansion condition
transmission: Power flow capacity between buses in preexpansion condition
plan: Planned amount
cg: Conventional generator
wg: Wind generator
l: Load
tl: Transmission line
shed: Load shedding
fuel1: Fuel source
fuel2: Fuel transportation
LP, UP: Lower bound/upper bound for interval model.

Parameters

B: Susceptance transmission lines
d: Discount rate
D: Distance
k: Coefficient associated with the worst realization
En: Energy generated by generators
FS: Fuel source capacity
FTL: Fuel transportation route capacity
GE: Allowable gaseous emission
HS: Duration of the peak load
Load: Forecasted peak load
MHO: Maximum hours of operation for generation unit
Pr: Price
α: Operation cost multiplier
β: Weighting parameter for each scenario
γ: Multiplier for gaseous emission
ɳ: Contribution factor for generation technology m
ψ: Fuel consumption multiplier for generation technology m
θ: Voltage angle in bus i in the preexpansion condition.

Variables

ELNS: Estimated energy not served
FT: Fuel transported between fuel sources and generating units
P: Power
U: Parameter which bounds the total cost in the robust model
ug: Binary decision variable for new conventional generation units
uw: Binary decision variable for new WF units
ut: Binary decision variable for new transmission lines
ud: Binary decision variable for demand response
ΔB: Changes in susceptance matrix compared to preexpansion condition

ΔP: Changes in power capacity of the newly installed elements
$\Delta\theta$: Changes in voltage angles compared to preexpansion condition
drr: Demand response rate
z: Objective function
λ: Probability degree
Υ: Weighting parameter.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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