Robust generation expansion planning considering high penetration renewable energies uncertainty

Omar H. Abdalla | Maged A. Abu Adma | Abdelmonem S. Ahmed

Electrical Power and Machines Engineering Department, Faculty of Engineering, Helwan University, Cairo, Egypt

Correspondence
Omar H. Abdalla, Electrical Power and Machines Engineering Department, Faculty of Engineering, Helwan University, Cairo, Egypt.
Email: ohabdalla@ieee.org

Abstract
The proper optimal generation expansion planning (GEP) should meet the reliability criteria requirements over a planning horizon under the presence of uncertainties. The intermittent nature of renewable energy sources (RES) introduces an enormous uncertainties impact within the planning model. A simulation model for RES uncertainty is developed using the capacity factor (CF) of the RES historical data. The RES simulation model is handled via the probability density function (PDF). The uncertainty parameter of different RES is described as a flexible polyhedral uncertainty set and incorporated within the proposed GEP model. The influence of different uncertainty scenarios for each RES uncertainty on the GEP model can be analyzed separately. The RES uncertainty scenarios are predefined and incorporated within the proposed GEP model through a proposed parameter named as a confidence level. The proposed confidence level parameter is beneficial to the power system planner to control the degree of robustness. Different GEP results are presented for various RES uncertainty scenarios. Three methods are proposed as appropriate solutions to deal with the RES uncertainty impact. The most economical method among the three proposed methods is determined by developing an objective function tailored to achieve the optimality of the economic factor.

KEYWORDS
energy storage system, generation expansion planning, renewable energy uncertainty, reserve margin, robust optimization

1 | INTRODUCTION

Generation expansion planning (GEP) is an essential study of power system planning. GEP is usually treated as an optimization problem intended for minimizing the total capital and operating costs associated with the new generation plants. The results of GEP are beneficial in determining the type, capacity, and the availability of new plants to be in service over a planning horizon. Furthermore, GEP being studied to meet the forecasted electricity demand with an appropriate degree of reliability to achieve the generation adequacy.1,2 The robust GEP model should take into account the impact of the inherent uncertainties. The planning uncertainty may be generated from forecasted load demand, electricity price,
operational and investment costs, fuel price, financial constraints, water flow for hydropower units, renewable energy penetration, transmission capacity, and environmental policies.\textsuperscript{3-11}

Climate change has resulted in a need for a rapid transition from fossil fuels to clean energy. Therefore, high penetration of RES with thermal resources becomes an essential requirement to maintain a sustainable future low carbon energy.\textsuperscript{12,13} However, the intermittent nature of RES has introduced a significant impact of uncertainties.\textsuperscript{14} Modeling the uncertainty parameter is essential to reveal the impact of uncertainty within the GEP models. Many methods are developed to model uncertainty data.\textsuperscript{15,16} The main difference between such methods depends on the uncertainty description method and the nature of uncertainty data. The existing uncertainty modeling techniques can be categorized as Information Gap Decision Theory (IGDT) technique,\textsuperscript{17} interval-based analysis,\textsuperscript{18} hybrid probabilistic and possibilistic methods,\textsuperscript{19} probabilistic methods,\textsuperscript{20} and robust set approaches.\textsuperscript{21} A scenario-based approach is proposed to analyze both demand and RES uncertainties in the network system.\textsuperscript{22} The proposed approach demonstrated that the consideration of uncertainties leads to an increase in the overall system costs to find a reasonable solution. Renewable energies and demand uncertainties are described through a robust set.\textsuperscript{23} The robust set is defined with different operating conditions via a multiscenario set. The probabilistic approach is useful in case a sufficient historical data of the system variables are available. Hence, the probabilistic approach is used to obtain the probability density function (PDF) for a variable with known or measured historical data. The historical data of wind and photovoltaic (PV) is used to predict uncertainties range via a developed prediction model.

Generally, the planning model under the presence of uncertainties is solved either by robust optimization (RO) or Stochastic Programming (SP). RO considers the worst-case scenario when dealing with uncertainty variables.\textsuperscript{24} RO is more conservative to maintain the feasibility than SP. However, the conservativeness of the results can be controlled. Both SP and RO are applied to deal with renewable energy uncertainties.\textsuperscript{25,26} The results validated that applying deterministic methodologies is insufficient to provide a robust solution. Therefore, most literature use SP and/or RO approaches to enhance the solution robustness. The handled uncertainties are described within the planning model through modeling an uncertainty set. The uncertainty set is commonly modeled as a region, box, ellipsoidal, and polyhedral.

The uncertainties caused by forecast errors of electrical demand and prices of new power system elements are modeled by the IGDT technique.\textsuperscript{17} The robust set of forecasted load, new generation plants, and transmission lines price uncertainties are maximized simultaneously. Reference 7 addressed the uncertainties of the RES and load forecast. The considered uncertainties are modeled as a box uncertainty set indicating the bounds of the uncertainties. The GEP model robustness can be effectively controlled by choosing an appropriate budget of the uncertainty set through preforming a sensitivity analysis test. The demand and available generation capacity uncertainties are modeled through an ellipsoidal uncertainty set.\textsuperscript{27} The level of conservativeness is controlled by proposing a conservativeness parameter defined by the network planner. The uncertainty boundaries are modeled as a polyhedral uncertainty set.\textsuperscript{5,11} The uncertainty of load, wind energy, and availability of generation plants is modeled in power system expansion planning.\textsuperscript{11} The robustness of the robust model is controlled by a particular parameter named the degree of robustness. The forecasted load, the investment, and operation costs uncertainties are considered in Reference 5. The degree of conservatism is adopted for each uncertainty set to control the degree of results robustness.

Many researchers used multiple uncertain budget.\textsuperscript{7,9,28} Each uncertainty has an uncertain budget. Consequently, the adjustable settings of each budget are increased and complicated its implementation within the practical application. References 5,8,11,27 proposed a single uncertain budget approach. The single uncertain budget is determined by certain network parameters such as a number of the planning horizon, candidate units, and load blocks. Accordingly, the value of the single uncertain budget is ranged from zero to the maximum value of the uncertain budget. Therefore, the effect of the budget change on the results can be clarified through a sensitivity analysis test. Thus, the network planner should carefully determine the appropriate budget of uncertainty set which affects the objective function cost.

The GEP model considered the capacity margin and LOLE to guarantee the security and reliability of the power system under the presence of RES uncertainties.\textsuperscript{29-31} A peaking reserve is used to tackle the uncertainty of wind power.\textsuperscript{32} Reference 2 described the RES implementation within the GEP model as thermal power plants with zero fuel cost and a high forced outage rate (FOR). The RES uncertainties are represented through the variation of the renewable output energy and incorporated into the GEP model through a FOR to reduce the RES capacity credit. Reference 33 studied the impact of the correlation between the different renewable plants’ uncertainties on the planning results. The correlated uncertainties are incorporated into the planning model through a devolved correlated polyhedral uncertainty set. References 2,33 proposed a reserve margin as an appropriate solution to cope with the uncertainty problem. The previously mentioned efforts\textsuperscript{2,29-33} proposed only the reserve margin solution to cope with the uncertainty problem.
This paper introduces a robust GEP model considering a high share of RES and shows the importance of considering the RES uncertainties within the proposed GEP model. The available historical data of wind and PV are used to predict the uncertainties via developing a representation model. RES uncertainties simulation model is handled by the PDF curve. Based on a predefined confidence level, various scenarios can be obtained from the PDF curve to clarify the influence of the weight of the uncertainties on the planning model. The uncertainties are incorporated into the planning model through a developed flexible polyhedral set. The boundaries of the polyhedral sets can be controlled based on an appropriate predefined parameter. Hence, the solution’s robustness is controlled. Analyzing the influence of each uncertainty weight will be beneficial for planners. A confidence level parameter is proposed to control the weight of each RES uncertainty set separately. A single uncertain budget will be investigated which is beneficial for practical implementation purposes and easily controlled. The single uncertain budget approach is predefined only once based on the weight of the uncertainty set. RES overcapacity, reserve margin, and energy storage system (ESS) methods are proposed to cope with the effect of RES uncertainty. The most appropriate method is determined through a tailored economic objective function.

The main contributions of this paper are as follows.

1. An analytical simulation model is developed to handle the estimated future RES uncertainty set accurately. The weight of each renewable uncertainty set can be controlled separately (i.e., the influence of different uncertainty scenarios for each uncertainty source on the GEP model can be analyzed separately).
2. Based on the uncertainty weight, a flexible polyhedral uncertainty set is developed to analyze the impact of uncertainty on the proposed robust GEP model. The degree of robustness is controlled through an adjustable robustness parameter that depends on the weights of each uncertainty set.
3. RES overcapacity, reserve margin, and ESS are introduced as effective methods to cope with the RES uncertainty problem. The optimal method is suggested based on technical and economic aspects.

The paper is organized as follows. Section 2 explains the RES uncertainty simulation model. Section 3 introduces the RO approach. The deterministic GEP model is introduced in Section 4. The robust GEP model is proposed in Section 5. Section 6 lists the used data and assumptions. GEP results are discussed in Section 7. Section 8 concludes the paper.

2 | LONG-TERM RES UNCERTAINTY SIMULATION MODEL

The simulation of the long-term RES uncertainty data can be depicted from the renewable historical data. RES historical data are used as input to calculate the annual CF for different renewable generation types. The historical data used for the simulation model depend on the renewable generation type, that is, wind speed data is used for wind farms and the solar radiation data is used for PV plants. The historical CF variation range indicates the range of historical uncertainty. Hence, historical uncertainty CF is beneficial to predict uncertainty range. The annual CF during the last 30 years of candidate wind and PV sites in Egypt are utilized to develop the simulation model. CF calculation is discussed in References 36, 37. Figure 1 shows the historical calculated annual CF for both wind and PV energy. The resulted statistical mean and SD of the calculated CF for wind energy is 31% and 2.8%, respectively, according to historical data shown in Figure 1.

For PV, mean and SD results are 18.5% and 0.62%, respectively. According to the mean and SD information, the corresponding uncertainty model of each renewable energy type is simulated by the PDF curve as shown in Figure 2.
3 | RO APPROACH

RO is one of the most known algorithms dealing with optimization problems under the presence of uncertainties. RO algorithm presents a worst-case optimal solution that is immunized against the uncertain parameters. The degree of the optimal solution robustness due to the uncertainties can be controlled via an adjustable robustness parameter. There are several definitions for uncertainty sets, which are defined as box, ellipsoidal, and polyhedral. The box set considers that all parameters will take the worst possible value. Hence, a high level of conservatism is achieved and causing deterioration for the objective function accordingly. To avoid the disadvantage of such over conservatism, polyhedral, and ellipsoidal uncertainty sets are proposed. The polyhedral is simple and less complex than the ellipsoidal. Therefore, RO induced by the polyhedral uncertainty set is utilized in this paper to describe and incorporate the RES uncertainty data into the GEP model. It is worth mentioning that, a flexible bounded-free polyhedral type is implemented in this paper to control the trade-off between robustness and performance.

3.1 | Flexible polyhedral uncertainty set

Flexible uncertainty set means that a variety of different amounts of each RES uncertainty source weight can be defined and implemented within the GEP model. Therefore, analyzing the influence of each uncertainty source will be beneficial for planners. Moreover, the boundaries of the uncertainty sets can be controlled based on an appropriate predefined parameter. Hence, the solution’s robustness is controlled. Figure 3 shows the geometric view of both the typical and flexible polyhedral uncertainty sets.

Figure 2: The PDF curve of: (A) wind capacity factor and (B) photovoltaic capacity factor

Figure 3: Typical and flexible polyhedral uncertainty sets
The flexible polyhedral is described in (1) as follows.

$$U_1 = \left\{ \|\xi\|_1 \leq \Gamma; \quad \Gamma = \sum_{j \in J} R_j \right\}, \quad (1)$$

where $\xi$ represents the random variable that is under uncertainty and distributed in the range $\xi \in [-R_j, R_j]$. $J$ is the cardinality whose corresponding coefficient is subject to uncertainty. $R_j$ is the ratio parameter that is defined as the ratio of the uncertainty amounted by a confidence level defined from the PDF of the uncertainty simulation model per the maximum expected value of the uncertainty. The ratio parameter is ranging between 0 and 1 ($0 \leq R_j \leq 1$). Figure 4 shows different predefined confidence levels scenarios (50%, 80%, and 99%) from the PDF based on historical calculated CF. It is noticed from Figure 4 that the uncertainty sets are flexible based on the confidence value. Therefore, the bounds of uncertainty become changeable and more independent.

3.2 RO counterpart based on flexible polyhedral uncertainty set

Reference 39 proposed the concept of robust counterpart optimization formulation for linear programming problem. Consider the following linear optimization problem as follows.

$$\text{Min} \ (cx), \quad (2)$$

$$\sum_{j \in J} \tilde{a}_{ij}x_j \leq b_i, \quad \forall i, \quad (3)$$

where $\tilde{a}_{ij}$ represents the constraint coefficient subject to uncertainties. The uncertain coefficients are described in (4) as follows.

$$\tilde{a}_{ij} = a_{ij} + \xi_{ij}\hat{a}_{ij}, \quad (4)$$

where $a_{ij}$ represents the mean value of the PDF curve and $\hat{a}_{ij}$ denotes the maximum range of uncertainty. So the main constraint (3) can be rewritten in (5) as follows.

$$\sum_{j \in J} a_{ij}x_j + \left[ \max_{i \in I} \left\{ \sum_{j \in J} \xi_{ij}\hat{a}_{ij}x_j \right\} \right] \leq b_i, \quad (5)$$

**FIGURE 4**  (A) Wind energy capacity factor with different confidence levels, (B) Photovoltaic capacity factor with different confidence levels and (C) flexible polyhedral uncertainty sets under different confidence levels (50%, 80%, and 99%)
where $U$ denotes the uncertainty set. If set $U$ is the flexible polyhedral, then the corresponding RO counterpart is equivalent to the following.

$$\sum_{j \in J} a_{ij} x_j + \Gamma L_i \leq b_i. \quad (6)$$

$$L_i \geq \tilde{a}_{ij}^{\max} |x_j|, \forall i. \quad (7)$$

$$\Gamma = \sum_{j \in J} R_{ij}. \quad (8)$$

### 4 | GEP MODEL PROBLEM FORMULATION

The main objective of the proposed GEP problem is to minimize the total system costs over a certain planning horizon. The minimization of the total costs includes thermal resources, renewable energy sources, energy not served, CO$_2$ emissions penalty, and the salvation value.

The proposed objective function is formulated in (9) as follows.

$$\min \frac{1}{(1 + r)^{T-1}} \sum_{t=1}^{T} \left[ C_{th}(t) + C_{RES}(t) + C_{ENS}(t) + C_{CO2}(t) - C_{SV}(t) \right]. \quad (9)$$

The equations represent each term in the objective function are explained as follows.

#### 4.1 | Thermal resources cost

The total investment, maintenance, and fuel costs of both candidate and existing thermal plants are defined in (10). The retirement of old inefficient plants is considered as well.

$$C_{th}(t) = \sum_{j=1}^{N_{th}} \left\{ \left[ I_{th}(t,j) P_{th}(j) X_{th}(t,j) \right] + \left[ F_{th}(t,j) E_{th}(t,j) X_{th}(t,j) \right] + \left[ F_{th}(t,j) \left[ Cap_{Exist}(t,j) - Cap_{Retire}(t,j) \right] \right] + \left[ OM_{th}(t,j) P_{th}(j) X_{th}(t,j) \right] + \left[ OM_{th}(t,j) \left[ P_{Exist}(t,j) - P_{Retire}(t,j) \right] \right] \right\}. \quad (10)$$

#### 4.2 | Renewable energy sources cost

Minimizing the total utility costs comprising the investment and maintenance costs of the candidate RES plants is formulated in (11) as follows:

$$C_{RES} = \sum_{i=1}^{N_{RE}} \left\{ \left[ I_{RE}(t,i) P_{RE}(i) X_{RE}(t,i) \right] + \left[ OM_{RE}(t,i) P_{RE}(i) X_{RE}(t,i) \right] \right\}. \quad (11)$$

#### 4.3 | Energy not served cost

Equation (12) aims to minimize the amount of energy expected not to be supplied in a given year.

$$C_{ENS} = |C_{ENS}(t) - ENS(t)|. \quad (12)$$
### 4.4 CO₂ emissions penalty cost

A carbon tax on the CO₂ emissions from thermal plants is considered as described in (13). The total cost of a CO₂ emission tax is counted for both the existing and planned thermal units.

\[
C_{\text{CO₂}} = \sum_{j=1}^{N_j} \left\{ \left[ \text{Tax}_{\text{CO₂}}(t) \ \text{EM}_{\text{CO₂}}(t, j) \ X_{\text{th}}(t, j) \right] + \left[ \frac{\text{Tax}_{\text{CO₂}}(t) \ \text{EM}_{\text{CO₂}}(t, j) \times \left[ \text{Cap}_{\text{Exist}}(t, j) - \text{Cap}_{\text{Retire}}(t, j) \right]}{\text{Cap}_{\text{Exist}}(t, j) - \text{Cap}_{\text{Retire}}(t, j)} \right] \right\}.  \tag{13}
\]

### 4.5 Salvation cost

The salvation value of the investment cost of both candidate thermal and renewable generating units is modeled and described in (14).

\[
C_{\text{SV}} = \sum_{j=1}^{N_j} \left[ \Omega(j) \ I_{\text{th}}(t, j) \ X_{\text{th}}(t, j) \right] + \sum_{i=1}^{N_i} \left[ \Omega(i) \ I_{\text{RE}}(t, i) \ X_{\text{RE}}(t, i) \right].  \tag{14}
\]

The equations describing the various constraints are detailed as follows.

The constraint (15) represents the power balancing equation. A predefined value of the reserve margin should be declared to meet the reliability and security requirements of the power system in case of unit outages.

\[
\sum_{t=1}^{T} \sum_{j=1}^{N_j} \left[ P_{\text{th}}(t) \ X_{\text{th}}(t, j) + \left[ P_{\text{Exist}}(t, j) - P_{\text{Retire}}(t, j) \right] \right] + \sum_{t=1}^{T} \sum_{i=1}^{N_i} \left[ P_{\text{RE}}(t, i) \ CF(i) \ X_{\text{RE}}(t, i) \right] \geq \sum_{t=1}^{T} \left[ P_{\text{D}}(t) \left( 1 + \frac{\text{Res}}{100} \right) \right].  \tag{15}
\]

The impact of a high share of RES integration, specifically wind and PV is incorporated in the GEP model as described in (16) and (17) as follows.

\[
\sum_{t=1}^{T} \sum_{i=1}^{N_i} \left[ P_{\text{RE}}(t, i) \ CF(i) \ X_{\text{RE}}(t, i) \right] = \sum_{t=1}^{T} \left[ P_{\text{D}}(t) \left( 1 + \frac{\text{Res}}{100} \right) \right].  \tag{16}
\]

\[
\Psi(t)(t + 1) \geq \left[ 1 + \frac{\text{RGR}}{100} \right] \Psi(t).  \tag{17}
\]

The LOLE should be guaranteed as described in (18).

\[
\text{LOLE}(t) \leq \text{LOLE}_{\text{limit}}.  \tag{18}
\]

As the reduction of the CO₂ emission has become an environmental mandatory requirement, the annual emission reduction rate is considered. The CO₂ constraints are represented in (19) and (20). The maximum amount of CO₂ is annually reduced as described in (20).

\[
\sum_{t=1}^{T} \sum_{j=1}^{N_j} \left[ \left[ \text{EMCO₂}(j) \ \text{EM}_{\text{CO₂}}(t, j) \ X_{\text{th}}(t, j) \right] + \left[ \text{EMCO₂}(j) \ \left[ \text{Cap}_{\text{Exist}}(t, j) - \text{Cap}_{\text{Retire}}(t, j) \right] \right] \right] \leq \sum_{t=1}^{T} \text{EMCO₂}(t)_{\text{limit}}.  \tag{19}
\]

\[
\text{EMCO₂}(t + 1)_{\text{limit}} \leq \left[ 1 - \frac{\text{ERR}}{100} \right] \text{EMCO₂}(t)_{\text{limit}}.  \tag{20}
\]
5 | ROBUST GEP MODEL

RES uncertainty creates imbalances between generation and load demand. Therefore, the effect of the RES uncertainty should be incorporated within the planning model. A RO approach is a perfect tool used to deal with problems under the presence of uncertainties. RES uncertainty impact is incorporated into the GEP model through developing a flexible polyhedral-based RO. The solution robustness is controlled based on a predefined confidence level. Renewable energy overcapacity, reserve margin, and ESS are proposed to cope with the RES uncertainty problem. The optimal method among the three proposed methods is determined by developing an economic objective function.

5.1 | Renewable energy overcapacity method

The power balancing constraint (15) and the high sharing RES integration constraint (16) are modified to represent the RES uncertainty as defined in (21), (22), and (23).

\[
\sum_{i=1}^{T} \sum_{j=1}^{N_{th}} \left[ P_{th}(j) X_{th}(t,j) \right] + \left[ P_{Exist}(t,j) - P_{Retire}(t,j) \right] \leq \sum_{i=1}^{T} \sum_{j=1}^{N_{RE}} \left[ P_{RE}(i) \bar{CF}(i) X_{RE}(t,i) \right] + \sum_{i=1}^{T} \left[ P_{D}(t) \left( 1 + \frac{\text{Res}}{100} \right) \right], \tag{21}
\]

\[
\sum_{i=1}^{T} \sum_{j=1}^{N_{RE}} \left[ P_{RE}(i) \bar{CF}(i) X_{RE}(t,i) \right] = \sum_{i=1}^{T} \Psi(t) \left[ P_{D}(t) \left( 1 + \frac{\text{Res}}{100} \right) \right] \tag{22}
\]

\[
\bar{CF}(i) = CF(i) + \xi \bar{CF}_{\text{max}}(i), \tag{23}
\]

where \( \bar{CF} \) is the capacity factor under uncertainty. \( CF \) is the capacity factor mean value. \( \bar{CF}_{\text{max}} \) is the maximum deviation of capacity factor (i.e., maximum range of uncertainty). \( \xi \) is distributed in the range \( \xi \in [-R_i, R_i] \). \( R_i \) is the ratio parameter which can be determined based on the confidence level of the CF uncertainty resulted from the PDF curve.

According to the RO counterpart induced by the flexible polyhedral uncertainty set, the constraints (21), (22), and (23) can be rewritten as follows.

\[
\sum_{i=1}^{T} \sum_{j=1}^{N_{th}} \left[ P_{th}(j) X_{th}(t,j) \right] + \left[ P_{Exist}(t,j) - P_{Retire}(t,j) \right] \leq \sum_{i=1}^{T} \sum_{j=1}^{N_{RE}} \left[ P_{RE}(i) \bar{CF}(i) X_{RE}(t,i) \right] + \sum_{i=1}^{T} \left[ P_{D}(t) \left( 1 + \frac{\text{Res}}{100} \right) \right], \tag{24}
\]

\[
\sum_{i=1}^{T} \left( \sum_{j=1}^{N_{RE}} \left[ P_{RE}(i) \bar{CF}(i) X_{RE}(t,i) \right] + \Gamma L_i \right) = \sum_{i=1}^{T} \Psi(t) \left[ P_{D}(t) \left( 1 + \frac{\text{Res}}{100} \right) \right]. \tag{25}
\]

\[
L_i \geq \left[ P_{RE}(i) \bar{CF}(i)_{\text{max}} X_{RE}(t,i) \right], \forall i. \tag{26}
\]

\[
\Gamma = \sum_{i \in N_{RE}} R_i. \tag{27}
\]

When applying the Mixed Integer Linear Programming (MILP) optimization technique on the robust GEP model through modified constraints (24), (25), (26), and (27), it is expected that the number of RES units \( X_{RE} \) will be increased to maintain the decrease in \( CF(i) \) due to the RES uncertainty based on the preselected confidence level.

5.2 | Reserve margin method

Reserve capacity is useful to preserve operational flexibility as well as maintain system reliability. Capacity margin is proposed to deal with the RES uncertainty. So that previous power balancing constraint (15) is modified and utilized as
The RES uncertainty is represented in the power balancing constraint (15) only in this method and not represented in the integration of high sharing RES constraint (16). The reason behind that the goal of this method is to deal with the RES uncertainty impact via increasing the number of thermal units $X_{ES}$ only as clarified in (24), (26), and (27). Hence, the reserve margin will be increased.

5.3 | Electrical ESS

ESS may be a preferable solution used by the grid operators to solve some of the critical characteristics of electricity generation and operation. Using ESS is beneficial for power system reliability and flexibility. An ESS is proposed as a solution to deal with the RES uncertainty problem.

Two stages are required to obtain the appropriate energy storage size and type. Firstly, the amount of annual power ($P_u$) required to cover the RES uncertainty should be determined. The amount of required power ($P_u$) is determined by calculating the difference between the amount of total power obtained from the GEP results without considering the RES uncertainty impact, in (15) and (16), and total power obtained from the GEP considering the RES uncertainty in (24), (25), (26), and (27). The amount of the required power ($P_u$) obtained from the first stage will be implemented in the second stage as a constraint. An objective function and technical constraints are developed in the second stage to determine the suitable energy type and the capacity of each type. The objective function is developed in (28) to minimize the total costs including investment and maintenance costs of candidate energy storage plants as follows.

$$\text{Min } \sum_{t=1}^{T} \sum_{k=1}^{N_{ESS}} \left\{ [I_{ESS}(t,k) P_{ESS}(k) X_{ESS}(t,k)] + [OM_{ESS}(t,k) P_{ESS}(k) X_{ESS}(t,k)] \right\}. \quad (28)$$

The sum of the planned energy storage plants must be greater than or equal to the electrical uncertainty power ($P_u$) in each year within the planning period to maintain the adequacy of the electrical power system as constrained in (29).

$$\sum_{t=1}^{T} \left( \sum_{k=1}^{N_{ESS}} [P_{ESS}(i) X_{ESS}(t,k)] \right) \geq \sum_{t=1}^{T} P_U(t). \quad (29)$$

5.4 | Determining the optimal method to cope with the RES uncertainty problem

In this section, the optimal economical method to deal with the RES uncertainty impact is determined. The three previously proposed methods are implemented within an objective function and appropriate constraint to achieve the optimality of the economic factor. The proposed objective function and the constraints are formulated in (30) and (31), respectively.

$$\text{Min } \frac{1}{(1+r)^{j-i}} \sum_{t=1}^{T} \left\{ \begin{array}{l} \sum_{j=1}^{N_{TH}} \left[ [I_{TH}(t,j) P_{TH}(j) X_{TH}(t,j)] + [F_{TH}(t,j) E_{TH}(t,j) X_{TH}(t,j)] \right] + [OM_{TH}(t,j) P_{TH}(j) X_{TH}(t,j)] \right\} + \sum_{i=1}^{N_{RE}} \left[ [I_{RE}(t,i) P_{RE}(i) X_{RE}(t,i)] + [OM_{RE}(t,i) P_{RE}(i) X_{RE}(t,i)] \right] + \sum_{k=1}^{N_{ESS}} \left[ [I_{ESS}(t,k) P_{ESS}(k) X_{ESS}(t,k)] + [OM_{ESS}(t,k) P_{ESS}(k) X_{ESS}(t,k)] \right] \right\}. \quad (30)$$
\[
\sum_{t=1}^{T} \sum_{j=1}^{N_{th}} [P_{th}(j) \cdot X_{th}(t,j)] + \sum_{t=1}^{T} \sum_{i=1}^{N_{RE}} [P_{RE}(i) \cdot CF(i) \cdot X_{RE}(t,i)] + \sum_{t=1}^{T} \sum_{k=1}^{N_{ESS}} [P_{ESS}(i) \cdot X_{ESS}(t,k)] \geq \sum_{t=1}^{T} P_U(t). \quad (31)
\]

6 DATA AND ASSUMPTIONS

According to the Egyptian power grid, the available candidate thermal plants for the case study are Combined Cycle Gas Turbine (CCGT), nuclear, and coal-fired. The available candidate renewable plants are PV and wind power plants. The candidate energy storage technologies are represented by Pumped Hydro Station (PHS), Compressed Air Energy Storage (CAES), and Lithium-ion (Li-ion) battery. The technical and economic characteristics of candidate thermal and renewable plants are shown in Table 1 while the energy storage technologies are shown in Table 2. The list of other assumptions is shown in Table 3. The forecasted peak load and energy demand over the planning period are shown in Figure 5. Figure 6 shows the retirement schedule of the existing plants. The planning horizon is assumed to be from the year 2021 up to 2040. A total of 35% of renewable energy sharing is aimed to be achieved by the end of 2040. The historical data of the wind and PV are attained from the New and Renewable Energy Authority46 and Renewables ninja.34,35 The carbon tax rate is varied from $0/ton to $30/ton with an incremental rate of $1.5/ton.41

**TABLE 1** Economic and technical characteristics of thermal and renewable plants41-43

|                     | CCGT | Coal | Nuclear | Photovoltaic | Wind |
|---------------------|------|------|---------|--------------|------|
| Rated power (MW/unit) | 400  | 600  | 1200    | 50           | 100  |
| Annual investment ($ (MW-year)^{-1}$) | 60 200 | 175 700 | 225 000 | 216 984 | 172 306 |
| OM cost ($ (MW-year)^{-1}$) | 25 270 | 43 650 | 58 630  | 23 900     | 39 700 |
| Fuel cost ($/MW)    | 42.42 | 23.12 | 11.8    | —           | —    |
| Forced outage rate  | 0.02  | 0.03  | 0.04    | 0.06        | 0.05 |
| Lifetime (year)     | 25    | 35    | 60      | 25          | 30   |
| CO2 emission (ton/MWh) | 0.4045 | 0.973 | 0.02 | —           | —    |

**TABLE 2** Economic and technical characteristics of energy storage technologies44,45

|                   | Pumped Hydro Station | Compressed Air Energy Storage | Li-ion |
|-------------------|----------------------|--------------------------------|--------|
| Rated power (MW/unit) | 200             | 200                            | 50     |
| Annual investment ($ (MW-year)^{-1}$) | 154 377        | 166 895                        | 463 370 |
| Fixed OM ($ (MW-year)^{-1}$) | 5236            | 4439                          | 7854   |
| Life time (year)   | 50                 | 30                            | 10     |

**TABLE 3** Assumptions data

| Symbol          | Value       |
|-----------------|-------------|
| RES             | 15%         |
| r               | 10%         |
| Ω               | 15%         |
| LOLE limit      | 8 hours/year|
| Renewable growth rate | 1%           |
7 | RESULTS AND DISCUSSION

Variety case studies are presented in this section based on the above-mentioned data and assumptions. The GEP is studied without considering the RES uncertainty impact and different cases considering the RES uncertainty. The obtained results clarify the impact of the uncertainty on the proposed GEP model. The GEP model is solved by MILP optimization technique.

7.1 | Total generation without considering uncertainty

The annual results of the capacity plants and the corresponding type over the proposed planning horizon are shown in Figure 7.

Various case studies considering the RES uncertainty impact in the proposed robust GEP model are conducted. The GEP results for the different proposed solutions to deal with the RES uncertainty impact are presented. RES uncertainties with different confidence level scenarios (50%, 80%, and 99%) are studied to clarify the influence of the RES uncertainty weight on the proposed robust GEP model. DIgSILENT Power Factory generation adequacy tool is used to verify the LOLE and the EENS of the GEP results.

7.2 | RES overcapacity method results

Figure 8 shows the RES overcapacity results for different RES uncertainty weights. The different RES uncertainty weights are based on the degree of confidence level. Increasing the confidence level resulted to increase the RES capacity as shown in Figure 8.
**Figure 7** Planning results without considering renewable energy sources uncertainty impact

**Figure 8** Impact of different renewable energy sources uncertainty weights on renewable capacity

**Figure 9** Impact of different renewable energy sources uncertainty weights on reserve margin capacity
7.3 | Reserve margin method results

In this case, reserve margin results for different RES uncertainty weights are shown in Figure 9.

7.4 | Electrical ESS method results

PHS, CASE, and Li-ion storage types are studied as ESS systems to cope with the RES uncertainty. The proposed objective function and constraints described by (28) and (29) resulted in the annual optimal number of each ESS type. The objective function resulted that PHS is the best economic solution of ESS types. Hence, CASE and Li-ion types are not recommended as a feasible ESS solution. Therefore, both types are not shown in Figure 10.

7.5 | Proposed optimal solution for RES uncertainty problem

Solving the objective function (30) resulted in using the ESS system is the most economical method to cope with the RES uncertainty. Moreover, from a technical point of view, ESS decreases the RES curtailment and enhances the grid operational flexibility.

7.6 | CO₂ gas emission reduction

The high tax rate value of CO₂ emission, as well as the high RES sharing, is constrained in the proposed GEP planning model. Therefore, it is observed from the results that the sharing percentage of the CO₂ gas emission is reduced while RES sharing is increased gradually as shown in Figure 11.
8 | CONCLUSION

A robust long-term GEP model is proposed in this paper considering the high sharing RES effect. A mathematical simulation model is developed to predict the long-term RES uncertainty to consider the uncertainty effect within the proposed GEP model. The PDF is used to handle the predicted uncertainty data to be described within the GEP model. A confidence level parameter is proposed to control the weight of each RES uncertainty set separately. The RES uncertainty is incorporated within the proposed GEP model through a flexible polyhedral to provide realistic and precise GEP results. The confidence level parameter is used to describe different RES uncertainty scenarios within the GEP model and control the degree of robustness. RES overcapacity, reserve margin, and ESS are proposed as three appropriate methods to deal with the uncertainty problem. The results of the three methods have demonstrated that increasing the confidence level resulted in increasing the RES capacity, total reserve margin, and the number of ESS. An economic objective function has been developed to determine the best solution among the three proposed methods. The results have shown that the use of PHS is the most economical method among all the proposed methods. The results obtained from the robust GEP model have validated the gradual CO$_2$ gas emission reduction and increasing the sharing of RES during the proposed planning horizon. The generation adequacy tool using DIgSILENT program has been used to verify the reliability criteria.

FUNCTIONS

- $C_{th}$: Thermal power plants cost.
- $C_{RES}$: Renewable sources cost.
- $C_{ENS}$: Energy not served cost.
- $C_{CO2}$: CO$_2$ emission penalty cost.
- $C_{sv}$: Salvation cost.

INDICES

- $t$: Planning years.
- $j$: Thermal plants types.
- $i$: Renewable plants types.
- $k$: Energy storage system types.

PARAMETERS

- $N_{th}$: Set of thermal plants types.
- $N_{RE}$: Set of renewable plants types.
- $N_{ESS}$: Set of energy storage system types.
- $T$: Set of planning years.
- $I_{th}$: Investment cost of thermal plants ($/MW$).
- $I_{RE}$: Investment cost of renewable plants ($/MW$).
- $I_{ESS}$: Investment cost of energy storage system ($/MW$).
- $P_{th}$: Rated power of thermal plants (MW).
- $P_{RE}$: Rated power of renewable plants (MW).
- $P_{Exist}$: Existing power of thermal plants (MW).
- $P_{Retire}$: Retirement power of thermal plants (MW).
- $P_{ESS}$: Rated power of energy storage system (MW).
- $F_{th}$: Fuel cost of thermal plants ($/MWh$).
- $E_{th}$: Output energy of thermal plants (MWh).
- $OM_{th}$: Operation and maintenance cost of thermal plants ($/MW$).
- $OM_{RE}$: Operation and maintenance cost of renewable plants ($/MW$).
- $OM_{ESS}$: Operation and maintenance cost of energy storage system ($/MW$).
- $Cap_{Exist}$: Existing capacity of thermal plants (MWh).
- $Cap_{Retire}$: Retirement capacity of thermal plants (MWh).
- $C_{ENS}$: Energy not served cost ($/MWh$).
- $EM_{CO2}$: CO$_2$ emission factor (ton/ MWh).
| Variable | Description |
|----------|-------------|
| EM\textsubscript{CO2 Limit} | Maximum Permissible CO\textsubscript{2} emission (ton/MWh). |
| Tax\textsubscript{CO2} | CO\textsubscript{2} emission tax ($/ton). |
| $\Omega$ | Salvage rate (%). |
| $P_D$ | Forecasted peak load (MW). |
| Res | Minimum reserve margin (%). |
| $\Psi$ | Annual growth rate of renewable power (%). |
| ERR | Emissions reduction rate (%). |
| RGR | Renewable growth rate (%). |
| $\Gamma$ | Adjustable robustness parameter. |
| LOLE | Loss of load expectation. |
| $r$ | The discount rate. |

**VARIABLES**

- $X_{RE}$: Number of required renewable plants.
- $X_{th}$: Number of required thermal plants.
- $X_{ESS}$: Number of required energy storage system plants.

**PEER REVIEW INFORMATION**

*Engineering Reports* thanks the anonymous reviewers for their contribution to the peer review of this work.

**CONFLICT OF INTEREST**

The authors have no conflict of interest.

**ORCID**

- [Omar H. Abdalla](https://orcid.org/0000-0002-8847-0829)
- [Abdelmonem S. Ahmed](https://orcid.org/0000-0002-5397-2415)

**REFERENCES**

1. Seifi H, Sepasian M. *Electric Power System Planning: Issues Algorithms and Solutions*. Berlin, Germany: Springer-Verlag; 2011.
2. Abdalla OH, Adma MAA, Ahmed AS. Generation expansion planning considering high share renewable energies uncertainty. Paper presented at: Proceedings of the 21st International Middle East Power Systems Conference (MEPCON); 2019:1-7; IEEE Xplore. doi:https://doi.org/10.1109/MEPCON47431.2019.9008180
3. Pereira AJC, Saraiva JT. A decision support system for generation expansion planning in competitive electricity markets. *Electr Pow Syst Res*. 2010;80(7):778-787. https://doi.org/10.1016/j.epsr.2009.12.003.
4. Zhan Y, Zheng QP, Wang J, Member S. Generation expansion planning with large amounts of wind power via decision-dependent stochastic programming. *IEEE Trans Power Syst*. 2017;32(4):3015-3026. https://doi.org/10.1109/TPWRS.2016.2626958.
5. Dehghan S, Amjady N, Kazemi A. Two-stage robust generation expansion planning: a mixed integer linear programming model. *IEEE Trans Power Syst*. 2014;29(2):584-597. https://doi.org/10.1109/TPWRS.2013.2287457.
6. Rebennack S. Generation expansion planning under uncertainty with emissions quotas. *Electr Pow Syst Res*. 2014;114:78-85. https://doi.org/10.1016/j.epsr.2014.04.010.
7. Han D, Wu W, Sun W, Yan Z. A two-stage robust stochastic programming approach for generation expansion planning of smart grids under uncertainties. *IEEE Power Energy Soc Gen Meet*. 2018;1-5. https://doi.org/10.1049/epsmg.2018.8586332.
8. Amjady N, Attarha A, Dehghan S, Conejo AJ. Adaptive robust expansion planning for a distribution network with DERs. *IEEE Trans Power Syst*. 2018;33(2):1698-1715. https://doi.org/10.1109/TPWRS.2017.2741443.
9. Baringo L, Baringo A. A stochastic adaptive robust optimization approach for the generation and transmission expansion planning. *IEEE Trans Power Syst*. 2018;33(1):792-802. https://doi.org/10.1109/TPWRS.2017.2713486.
10. Hamidpour H, Aghaei J, Pirouzi S, Dehghan S, Niknam T. Flexible, reliable, and renewable power system resource expansion planning considering energy storage systems and demand response programs. *IET Renew Power Gener*. 2019;13(11):1862-1872. https://doi.org/10.1049/iet-rpg.2019.0020.
11. Dehghan S, Amjady N, Conejo AJ. Reliability-constrained robust power system expansion planning. *IEEE Trans Power Syst*. 2016;31(3):2383-2392. https://doi.org/10.1109/TPWRS.2015.2464274.
12. Al-Riyami HA, Al-Busaidi A, Al-Nadabi A, Al-Sayabi MN, Abdalla OH. Planning studies for connection of 500 MW photovoltaic power plant to Oman Grid at Ibbi. Paper presented at: Proceedings of the 14th GCC Cigre International Conference, Paper A302, GCC Power, Kuwait; 11–13 November 2018:1-11. http://works.bepress.com/omar/53/.
13. Dominguez R, Member S, Conejo AJ, Carrión M. Toward fully renewable electric energy systems. *IEEE Trans Power Syst*. 2015;30(1):316-326. https://doi.org/10.1109/TPWRS.2014.2322909.
14. Khalaf AA. Challenges and benefits of integrating the renewable energy technologies into the AC power system grid. *Am J Eng Res*. 2017;6:95-100. www.ajer.org.

15. Jordehi AR. How to deal with uncertainties in electric power systems? A Rev *Renew Sustain Energy Rev*. 2018;96:145-155. https://doi.org/10.1016/j.rser.2018.07.056.

16. Aien M, Rashidinejad M, Fotuhi-Firuzabad M. On possibilistic and probabilistic uncertainty assessment of power flow problem: a review and a new approach. *Renew Sustain Energy Rev*. 2014;37:883-895. https://doi.org/10.1016/j.rser.2014.05.063.

17. Kendziorski M, Setje-eilers M, Kunz F. Generation expansion planning under uncertainty: an application of stochastic methods to the German electricity system. Paper presented at: Proceedings of the 2017 14th International Conference on the European Energy Market (EEM); 2017:1-7; Dresden, Germany. doi:https://doi.org/10.1109/EEM.2017.7981891

18. De Oliveira LW, Seta FS, De Oliveira EJ. Electrical power and energy systems optimal reconfiguration of distribution systems with representation of uncertainties through interval analysis. *Int J Electr Power Energy Syst*. 2016;83:382-391. https://doi.org/10.1016/j.ijepes.2016.04.020.

19. Staffell I, Pfenninger S. Using bias-corrected reanalysis to simulate current and future wind power output. *Energy*. 2016;114:1224-1239. https://doi.org/10.1016/j.energy.2016.08.068.

20. Li J, Li Z, Liu F, Ye H. Robust coordinated transmission and generation expansion planning considering uncertain and random weight of network. *Appl Energy*. 2018;219:207-225. https://doi.org/10.1016/j.apenergy.2018.03.023.

21. Xie S, Hu Z, Wang J. Two-stage robust optimization for expansion planning of active distribution systems coupled with urban transportation networks. *Appl Energy*. 2020;261:114412. https://doi.org/10.1016/j.apenergy.2019.114412.

22. Li J, Li Z, Liu F, Ye H. Robust coordinated transmission and generation expansion planning considering ramping requirements and construction periods. *IEEE Trans Power Syst*. 2017;33(1):268-280. https://doi.org/10.1109/tpwrs.2017.2687318.

23. Hemmati R, Hooshmand R, Khodabakhshian A. Coordinated generation and transmission expansion planning in deregulated electricity market considering wind farms uncertainties in deregulated electricity market. *Energ Conver Manage*. 2016;114:1224-1239. https://doi.org/10.1016/j.enconman.2016.09.002.

24. Xie S, Hu ZZ, Wang J, et al. Short-term uncertainty in long-term energy system models - a case study of wind power in Denmark. *Energy Econ*. 2015;49(5):157-167. https://doi.org/10.1016/j.eneco.2015.02.004.

25. Abdalla OH, Adma MAA, Ahmed AS. Generation expansion planning under correlated uncertainty. *IEEE Trans Power Syst*. 2018;33(3):2071-2082. https://doi.org/10.1109/TPWRS.2018.2889032.

26. Ruiz C, Conejo AJ. Robust transmission expansion planning. *Eur J Oper Res*. 2015;242(2):390-401. https://doi.org/10.1016/j.ejor.2014.10.030.

27. Hemmati R, Hooshmand R, Khodabakhshian A. Coordinated generation and transmission expansion planning in deregulated electricity market considering wind farms. *Renew Energy*. 2016;85:620. https://doi.org/10.1016/j.renene.2015.07.019.

28. Hemmati R, Hooshmand RA, Khodabakhshian A. Reliability constrained generation expansion planning with consideration of wind farms uncertainties in deregulated electricity market. *Energ Conver Manage*. 2013;76:517-526. https://doi.org/10.1016/j.enconman.2013.08.002.

29. Huang Y, Hu J, Yang Y, Yang L, Liu S. A low-carbon generation expansion planning model considering carbon trading and green certificate transaction mechanisms. *Polish J Environ Stud*. 2020;29(2):1169-1183. https://doi.org/10.15244/pjes/106025.

30. Xie S, Hu ZZ, Wang J, et al. Short-term uncertainty in long-term energy system models - a case study of wind power in Denmark. *Energy Econ*. 2015;49(5):157-167. https://doi.org/10.1016/j.eneco.2015.02.004.

31. Abdalla OH, Adma MAA, Ahmed AS. Generation expansion planning under correlated uncertainty of mass penetration renewable energy sources. *IET Energy Syst Integr*. 2020;2:1-10. https://doi.org/10.1049/iet-esi.2020.0008.

32. Pfenninger S, Staffell I, Pfenninger S. Using bias-corrected reanalysis to simulate current and future wind power output. *Energy*. 2016;114:1224-1239. https://doi.org/10.1016/j.energy.2016.08.068.

33. Pfenninger S, Staffell I. Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. *Energy*. 2016;114:1251-1265. https://doi.org/10.1016/j.energy.2016.08.060.

34. Wu W, Hu Z, Song Y, Sansavini G, Chen H, Chen X. Transmission network expansion planning based on chronological evaluation considering wind power uncertainties. *IEEE Trans Power Syst*. 2018;33(5):4787-4796. https://doi.org/10.1109/TPWRS.2018.2809728.

35. Keles C, Alagoz BB, Akcin M, Kaygusuz A, Karabiber A. A photovoltaic system model for matlab / simulink simulations. Paper presented at: Proceedings of the 4th International Conference on Power Engineering, Energy and Electrical Drives; 2013:1643-1647; IEEE. https://doi.org/10.1109/PowerEng.2013.6635863.

36. Li Z, Ding R, Floudas CA. A comparative theoretical and computational study on robust counterpart optimization I: robust linear optimization and robust mixed integer linear optimization. *Ind Eng Chem Res*. 2011;50(18):10567-10603. https://doi.org/10.1021/ie200150p.

37. Zhang Y, Feng Y, Rong G. New robust optimization approach induced by flexible uncertainty set: optimization under continuous uncertainty. *Ind Eng Chem Res*. 2017;56(1):270-287. https://doi.org/10.1021/acs.iecr.6b02989.

38. Li Z, Floudas CA. A comparative theoretical and computational study on robust counterpart optimization: III. improving the quality of robust solutions. *Ind Eng Chem Res*. 2014;53(33):13112-13124. https://doi.org/10.1021/ie501898n.
How to cite this article: Abdalla OH, Abu Adma MA, Ahmed AS. Robust generation expansion planning considering high penetration renewable energies uncertainty. Engineering Reports. 2020;2:e12187. https://doi.org/10.1002/eng2.12187