This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSTE.2018.2789398, IEEE Transactions on Sustainable Energy

Bundled Generation and Transmission Planning under Demand and Wind Generation Uncertainty based on a Combination of Robust and Stochastic Optimization

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***Abstract*—Bundled generation and transmission expansion planning (BGTEP) aims to solve problems related to ascendant demand of power systems. A BGTEP model is considered in this paper and the optimal planning for a long-term period is obtained such that the cost of installation and operation would be minimized. Also, due to the recent orientation towards renewable energy sources (RES), the influence of wind farms is involved in the methodology. An important aspect of load and wind power is their uncertain nature and the characteristic of being unforeseen. This matter is under consideration by a bounded and symmetric uncertainty optimization approach. In fact, the combination of two uncertainty methods, i.e., robust and stochastic optimization approaches are utilized and formulated in this paper. Besides, to cope with this uncertainty, Weibull Distribution (WD) is considered as wind distribution, while load distribution is counted by a Normal Distribution (ND). An unique approximation approach for WD to be considered as ND is presented. In addition, a linear formulation is obtained by alternative constraints in order to drastically reduce the level of complexity of the formulation. Accordingly, a Mixed Integer Linear Programming (MILP) formulation is proposed to solve the BGTEP problem. The modified 6-bus and IEEE 24-bus RTS test systems are used to prove the applicability of the proposed method.**

***Index Terms*—Bundled Generation and Transmission Expansion Planning (BGTEP), Bounded Symmetric Optimization (BSO), Mixed Integer Linear Programming (MILP), Robust Optimization (RO), Normal Distribution (ND), Weibull Distribution (WD)**

NOMENCLATURE

A. Indices and Sets

$\phi_{\ln}$	Set of candidate lines.
ϕ_{in}	Set of candidate units.
ϕ_t	Set of demand intervals.
ϕ_i	Set of candidate and existing units.
ϕ_l	Set of candidate and existing lines.
φ_n^i	Set of units placed at bus n.
φ_n^j	Set of loads placed at bus n.
γ_k	Set of components of disabled due to contingency k.
ζ	Set of all candidate and existing components covering units and lines.
$s(l)$	Sending bus of line l.
$r(l)$	Receiving bus of line l.

B. Constants

IC_l	Investment cost of candidate line l (\$).
IC_i	Investment cost of candidate unit i (\$).
du_t	Duration of demand interval t (hour).
OM_i	Operation and maintenance cost of unit i (\$/MWh).
$p_i^{\max}$	Maximum output power of unit i (MW).
L_{jt}^f	Value of forecast load j at demand interval t (MW).
pw_{jt}^f	Value of forecast wind power at bus n related to load j in the demand interval t (MW).
X_l	Reactance of line l.
$f_l^{\max}$	Maximum power flow of line l (MW).
R	Forced outage rate.

C. Variables

b_l	Binary variable that for constructed line l is equal to 1 and 0 otherwise
b_i	Binary variable that for constructed unit i is equal to 1 and 0 otherwise
p_{it}	Output power of unit i in the demand interval t (MW).
$\theta_{n,t}$	Voltage angle of bus n under demand interval t.

J.P.S. Catalão acknowledges the support by FEDER funds through COMPETE 2020 and by Portuguese funds through FCT, under Projects SAICT-PAC/0004/2015 - POCI-01-0145-FEDER-016434, POCI-01-0145-FEDER-006961, UID/EEA/50014/2013, UID/CEC/50021/2013, and UID/EMS/00151/2013, and also funding from the EU 7th Framework Programme FP7/2007-2013 under GA no. 309048.

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f_{lt} Flow power of line l in the demand interval t (MW).

τ_{jtk} Load shedding of load j at demand interval t under contingency k.

Ω_0 Availability probability of component without contingency.

Ω_k Probability of contingency k.

EENS_{jtk} Expected energy not supplied at load j in the demand interval t under contingency k.

I. INTRODUCTION

A. Aims and Background

THE extension of the entire network has been introduced as an important issue in recent years. Considering the new components which can be installed in order to supply the extra loads culminates in bundled generation and transmission expansion planning (BGTEP) [1], [2]. In this problem, it should be decided when to invest new capacity and which kind of generation or transmission is needed. Moreover, in the BGTEP problem the optimum location of the newly constructed components should be assessed [3]. It is a foregone conclusion that, as time passes, the number of devices which ought to be supplied increases.

The final goal of BGTEP is to have a secure reliability level for the forecasted electricity demand. In this situation, the generation and transmission constraints should be satisfied. In addition, the amount of emissions corresponding to greenhouse gases is progressively increasing, thus renewable energies are being increasingly used in order to create a friendlier climate. Renewable Energy Sources (RES) such as wind power and solar cells are clean sources. However, their associated generation shows inherent uncertainty [4], [5].

B. Literature Review

To cope with the above-mentioned challenge, the topic of BGTEP has been gaining the attention of the research community. In [6] superconducting fault current limiters are implemented to decrease the current faults in a model of combined generation and transmission network expansion planning. There are several methodologies for solving a multi-objective BGTEP model. In addition to the cost, the reliability is another objective function for [7], where a multi-objective probabilistic expansion model is solved. Another multi-objective transmission expansion planning that covers the uncertain investment budget and uncertain demand is shown in [8].

Currently, significant research focusing on separate generation or transmission expansion planning has been published. Indeed, Generation Expansion Planning (GEP) is considered as the main objective in some works in the area [9]–[11].

In [9] the application of stochastic MILP is considered in multi-stages (periods), and the uncertainty of hydrological resources are analyzed. In [10] a GEP problem is solved while the effect of different units such as nuclear, renewable energy and different fossil fuel-fired units is considered. A co-optimizing methodology in the form of charging or discharging of electric vehicles is proposed in [11].

Recently, the investors have unprecedented challenges on Transmission Expansion Planning (TEP), thus the authors solve this problem with several different points of view [12]–[14]. In [12] TEP problem is solved by implementing a multi-objective framework considering cost and risk as two contradictory goals. The authors in [13] propose a method utilizing the power transfer distribution factors by which some important transmission lines would be observable, and afterwards, they try to create a reliable system. A short-circuit level constrained TEP problem is analyzed in [14] where a MILP approach is used by considering the transmission investment cost as a master problem with three different sub problems. The inherent uncertainties such as load uncertainty and unforeseen wind power have been challenged by the authors in many published types of research. The robust optimization (RO) method is a prevalent approach for the purpose of studying the forecasting uncertainty of the load or renewable sources [15]–[17]. In [15] a scenario-based RO is implemented to cope with the load and wind uncertainty for the TEP problem. Similarly, a single and two-stage robust optimization is used in [16] to solve the uncertainty of the GEP problem. Likewise, the authors in [17] present a robust optimization while abstaining from employing the traditional probabilistic model used in stochastic approaches. In fact, there is no need for the probability distribution functions of the uncertain parameters in the RO methodology.

C. Contribution

In this paper the problem of expansion planning regarding the lines and generators is formulated while the wind turbine is considered as a renewable source. In the presence of network uncertainties the complexity of expansion planning problem increases. Here uncertainties are related to a variety of wind velocity culminating in varied wind power and in the diversity of demand. RO and stochastic programming (SP) are two different methods which are implemented to cope with the system's uncertainty nature. However, the proposed method is based on a combination of RO and SP. Additionally, the wind power is estimated by Weibull Probability Distribution Function (WPDF). However, since the combination of RO and SP requires the uncertain variable to have a Normal Probability Distribution Function (NPDF), then a new approximation methodology considering WPDF as an NPDF with a minimum error is used in the proposed approach. In fact, the suggested methodology approximates the Weibull distribution (pertaining to the wind turbine) to the normal distribution with the specified mean and standard deviation which is the closest distribution to WPD, and no other NPDF which has an error less than the error calculated in the proposed approximation exists. Therefore, by this approximation and considering the wind power by the NPDF which is the closest distribution to WPD, the bounded and symmetric approach can be $\forall l, \forall t$ integrated while the effect of the uncertain wind power is covered.

Although in [15]–[17] the RO strategy has been presented for the TEP and GEP problems, the symmetric aspect of uncertainty related to the stochastic problem has not been addressed in these works. To the best authors' knowledge, finding the best approximation of the Weibull to Normal distribution is not considered in the previous research.

II. Mathematical Formulation

In this section the BGTEP problem is formulated and an objective function containing the operation and investment cost is minimized. In addition, the expected energy that is not supplied (EENS) as well as the probabilistic reliability criteria are added to the objective function. Meanwhile, technical and operational constraints should be satisfied.

A. Problem Formulation without Wind

The investment cost for constructed units and new lines as well as the operation cost of existing units should be minimized as follows [18], [19]:

$$Cost = \sum_{l\in\phi_{\ln}} b_l IC_l + \sum_{i\in\phi_{in}} b_i IC_i + \sum_{t\in\phi_t}\sum_{i\in\phi_i} p_{it} OM_i du_t \quad (1)$$

The first two terms are related to the investment cost (C_{inv}), and the third term relates to operation cost (C_{gen}). The constraints are given below [20], [21]:

$$b_l = 1 \qquad \forall l \in \{\phi_l - \phi_{\ln}\} \quad (2)$$

$$b_i = 1 \qquad \forall i \in \{\phi_i - \phi_{in}\} \quad (3)$$

$$b_l \in \{0,1\} \qquad \forall l \in \phi_{\ln} \quad (4)$$

$$b_i \in \{0,1\} \qquad \forall i \in \phi_{in} \quad (5)$$

$$0 \le p_{it} \le b_i p_i^{\max} \qquad \forall i, \forall t \quad (6)$$

$$\sum_{i\in\varphi_n^i} p_{it} - \sum_{l:s(l)=n} f_{lt} + \sum_{l:r(l)=n} f_{lt} = 0 \qquad \forall n \notin \varphi_n^j, \forall t \quad (7)$$

$$\sum_{i\in\varphi_n^i} p_{it} - \sum_{l:s(l)=n} f_{lt} + \sum_{l:r(l)=n} f_{lt} \ge \sum_{j\in\varphi_n^j} L_{jt}^f \qquad \forall n \in \varphi_n^j, \forall t \quad (8)$$

$$\sum_{i\in\varphi_n^i} p_{it} - \sum_{l:s(l)=n} f_{lt} + \sum_{l:r(l)=n} f_{lt} \le \sum_{j\in\varphi_n^j} L_{jt}^f + \delta \sum_{j\in\varphi_n^j} L_{jt}^f - \varepsilon\lambda \sum_{j\in\varphi_n^j} L_{jt}^f \qquad \forall n \in \varphi_n^j, \forall t \quad (9)$$

$$f_{lt} = \frac{b_l}{X_l}(\theta_{s(l),t} - \theta_{r(l),t}) \qquad \forall l, \forall t \quad (10)$$

$$f_{lt} \le f_l^{\max} \qquad \forall l, \forall t \quad (11)$$

$$f_{lt} \ge -f_l^{\max} \qquad \forall l, \forall t \quad (12)$$

The constraints (2) and (3) belong to the binary variables of the existing elements. The constraints (4) and (5) describe the situation of the new components, if b_l=1 and b_i=1, new components have been added to the system or otherwise b_l=0 and b_i=0. Constraint (6) states the power limitations of the generators. Constraint (7) states the balance equation for buses without load. Constraint (8) states the balance equation for buses with the load that is relaxed [20], [21]. In fact, the balance equation represents the difference of generation power and sending power at each bus is equal to consumption in that bus. Constraint (9) is the same as the balance equation by considering the uncertain demand j at the period t where ε denotes the uncertainty level. δ denotes the infeasibility tolerance, and the relationship between λ and κ (reliability level) is given as follows:

$$\kappa = 1 - F(\lambda) \quad (13)$$

$$\kappa = 1 - \Pr\{\Psi \le \lambda\} \quad (14)$$

$$\Psi = -\xi \quad (15)$$

$$\kappa = 1 - \int_{-\infty}^{\lambda} \frac{1}{\sqrt{2\pi}} \exp(-\frac{x^2}{2}) dx \quad (16)$$

In the proposed method $\delta \ge \varepsilon\lambda$ and λ is between -1 and 1. Constraint (10) represents the power flow of the lines. Constraints (11) and (12) are the limitations of the power flow. By facing the contingency the EENS is added and will have the following:

$$0 \le p_{itk} \le b_i p_i^{\max} \qquad \forall i, \forall t, \forall k \quad (17)$$

$$\sum_{j\in\varphi_n^j} \tau_{jtk} \ge \sum_{j\in\varphi_n^j} L_{jt}^f - \sum_{\substack{i\in\varphi_n^i\\ i\notin\gamma_k}} p_{itk} + \sum_{\substack{l:s(l)=n\\ l\notin\gamma_k}} f_{ltk} - \sum_{\substack{l:r(l)=n\\ l\notin\gamma_k}} f_{ltk} \qquad \forall n \notin \varphi_n^j, \forall t, \forall k \quad (18)$$

$$\sum_{j\in\varphi_n^j} \tau_{jtk} \le \sum_{j\in\varphi_n^j} L_{jt}^f + \delta\sum_{j\in\varphi_n^j} L_{jt}^f - \varepsilon\lambda\sum_{j\in\varphi_n^j} L_{jt}^f - \sum_{\substack{i\in\varphi_n^i\\ i\notin\gamma_k}} p_{itk} + \sum_{\substack{l:s(l)=n\\ l\notin\gamma_k}} f_{ltk} - \sum_{\substack{l:r(l)=n\\ l\notin\gamma_k}} f_{ltk} \qquad \forall n \notin \varphi_n^j, \forall t, \forall k \quad (19)$$

$$f_{ltk} = \frac{b_l}{X_l}(\theta_{s(l)tk} - \theta_{r(l)tk}) \qquad \forall l, \forall t, \forall k \quad (20)$$

$$f_{ltk} \le f_l^{\max} \qquad \forall l, \forall t, \forall k \quad (21)$$

$$f_{ltk} \ge -f_l^{\max} \qquad \forall l, \forall t, \forall k \quad (22)$$

Constraint (17) is the unit of power limitations. τ_{jtk} is the lost load pertaining to the load j at bus n at the period t under contingency k and it was seen in constraint (18) that is relaxed. Additionally, the difference between the forecasting load with generation power and receiving power at each bus represents the lost load. τ_{jtk} is defined as load shedding. Constraint (19) is the same as the previous constraint by considering the uncertainty of demand. Constraints (20)-(22) are the power flow and the limitations of the line under contingency.

A binary variable that describes the state of the total components is defined as following:

$$\boldsymbol{\omega}_{1\times K} = [\boldsymbol{\omega_e}\ \boldsymbol{\omega_n}] \quad (23)$$

ω_e is related to the existing components and is one. ω_n denotes the state of the new components and is one or zero. ω_n at Built-in components is 1, otherwise ω_n=0.

Access or lack of access to components makes it a binomial probability distribution and is defined as the Bernoulli distribution [22]:

$$\Omega_0 = \prod_{\alpha\in\zeta}(1 - \omega_\alpha R_\alpha) \quad (24)$$

$$\Omega_k = \omega_k R_k \prod_{\substack{\omega\ne k\\ \omega\in\zeta}}(1 - \omega_w R_w) = \omega_k R_k (1-R_k)^{-1} \prod_{\omega\in\zeta}(1 - \omega_w R_w) = \omega_k R_k (1-R_k)^{-1}\Omega_0 \qquad \forall k \quad (25)$$

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where R_α is defined as the forced outage rate (FOR) of the element α. The Eq. (24) states the probability of availability of the elements in non-contingent status. The Eq. (25) denotes the probability of the contingency k.

The EENS at the load j, during period t under contingency k, is as follows:

$$\text{EENS}_{jtk} = \Omega_k \tau_{jtk} du_t \qquad \forall j, \forall t, \forall k \tag{26}$$

The cost of EENS is defined as:

$$Cost_{EENS} = \text{VOLL} \times \sum_k \sum_{t \in \phi_t} \sum_{j \in \phi_d} \Omega_k \tau_{jtk} du_t \tag{27}$$

where the value of the lost load (VOLL) is found in [23]. Also, by considering the contingency, the objective function is written as:

$$\min \left\{ \begin{aligned} & C_{inv} + \Omega_0 C_{gen} + \sum_k \Omega_k \left(\sum_{t \in \phi_t} \sum_{\substack{i \in \phi_i \\ i \notin \gamma_k}} p_{itk} OM_i du_t \right) + \\ & Cost_{EENS} \end{aligned} \right\} \tag{28}$$

B. Problem Formulation with Wind

Adding wind power to the system will affect the constraints (8), (9), (18), (19). This impact is given as follows:

$$\sum_{i \in \varphi_n^i} p_{it} - \sum_{l:s(l)=n} f_{lt} + \sum_{l:r(l)=n} f_{lt} \ge P_{ND}^f \qquad \forall n \in \varphi_n^j, \forall t \tag{29}$$

$$\begin{aligned} & \sum_{i \in \varphi_n^i} p_{it} - \sum_{l:s(l)=n} f_{lt} + \sum_{l:r(l)=n} f_{lt} \le P_{ND}^f \\ & + \delta P_{ND}^f - \varepsilon \lambda P_{ND}^f \end{aligned} \qquad \forall n \in \varphi_n^j, \forall t \tag{30}$$

$$\begin{aligned} & \sum_{j \in \varphi_n^j} \tau_{jtk} \ge P_{ND}^f \\ & - \sum_{\substack{i \in \varphi_n^i \\ i \notin \gamma_k}} p_{itk} + \sum_{\substack{l:s(l)=n \\ l \notin \gamma_k}} f_{ltk} - \sum_{\substack{l:r(l)=n \\ l \notin \gamma_k}} f_{ltk} \end{aligned} \qquad \forall n \in \varphi_n^j, \forall t, \forall k \tag{31}$$

$$\begin{aligned} & \sum_{j \in \varphi_n^j} \tau_{jtk} \le P_{ND}^f \\ & + \delta P_{ND}^f - \varepsilon \lambda P_{ND}^f \\ & - \sum_{\substack{i \in \varphi_n^i \\ i \notin \gamma_k}} p_{itk} + \sum_{\substack{l:s(l)=n \\ l \notin \gamma_k}} f_{ltk} - \sum_{\substack{l:r(l)=n \\ l \notin \gamma_k}} f_{ltk} \end{aligned} \qquad \forall n \in \varphi_n^j, \forall t, \forall k \tag{32}$$

$$P_{ND}^f = \sum_{j \in \varphi_n^j} (L_{jt}^f - pw_{jt}^f) \qquad \forall n \in \varphi_n^j, \forall t \tag{33}$$

Constraint (29) is similar to constraint (8) which is relaxed and constraint (30) is the same as constraint (29) by considering the uncertainty of the demand and wind power. In fact, with the wind generation to the network, these two constraints replace the constraints (8) and (9). Constraint (31) is the amount of load shedding in which the impact of wind power in P^f_{ND} appears and constraint (32) is considers the uncertainty of the demand and wind power. These two constraints also replace the constraints (18) and (19). The difference of the forecasting load and wind power is defined as the forecasting net demand power (P^f_{ND}) at constraint (33).

III. Approximation of WPDF to NPDF

In order to use the mentioned approach, the uncertain parameter should be described by a normal distribution [20], [21]. In the previous section, the difference between load and wind power was defined as the net demand power. The load is defined by a normal distribution, but the distribution of wind power isn't. Empirical observations of the wind power in wind farms can be considered as a normal distribution [24]. According to the empirical wind data and a curve fitting, it is observed that the single-Weibull, bi-Weibull or tri-Weibull distributions are good approximations for the available wind data. Using Akaike information criterion (AIC) and Bayesian information criterion (BIC), it can be determined which of these three distributions are much more suitable for the available wind data [25].

The data of the Weibull distribution mixture is found in [25]. So should the wind power distribution, approximated by a normal distribution and then benefitted from the approach of a combination of RO and SP. In this section, the distribution of wind power in three states (one, two and three Weibull) is approximated by the normal distribution. The WPDF is expressed as:

$$f(x) = \frac{\hbar}{\rho} \left(\frac{x}{\rho}\right)^{\hbar - 1} \exp^{\left(-\left(\frac{x}{\rho}\right)^{\hbar}\right)} \tag{34}$$

where ρ and $\hbar$ are the Weibull scale parameter and shape parameter, respectively.

The Weibull distribution mixture of wind power is given following:

$$f(pw) = \sum_{N=1}^{c} \Gamma_N f(pw \mid \varpi_N) \tag{35}$$

where Γ_N is the weight of each term, N is the number of terms, $f(pw|\varpi_N)$ is the Weibull distribution function, where in ϖ is included ρ and $\hbar$. However, the WPDF should be approximated by a NPDF in which the error is lower than any other NPDF. This approximation is obtained by the following error:

$$Error = \left| \begin{aligned} & \left(\sum_{z=1}^{c} \Gamma_z f(pw \mid \varpi_N) \right) \\ & - \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-0.5 \left(\frac{pw - \mu}{\sigma} \right)^2 \right) \end{aligned} \right| \tag{36}$$

The second term of the error is NPDF where σ and μ are the standard deviation and expected value, respectively. The error acquires the difference between WPDF and the specified NPDF. It also determines the maximum difference. This procedure is applied for different NPDFs and each time the maximum difference is determined. Between these maximum differences the minimum value is selected. The selected value is related to a specified NPDF. It is the best approximation for the WPDF of the wind power.

A. Approximation of the Single Weibull Distribution

If c=1, then the wind power distribution is a single Weibull in which the parameters contain: ρ=33.86, $\hbar$=1.95. The approximation of the single Weibull to a specified NPDF is shown in Fig. 1(a).

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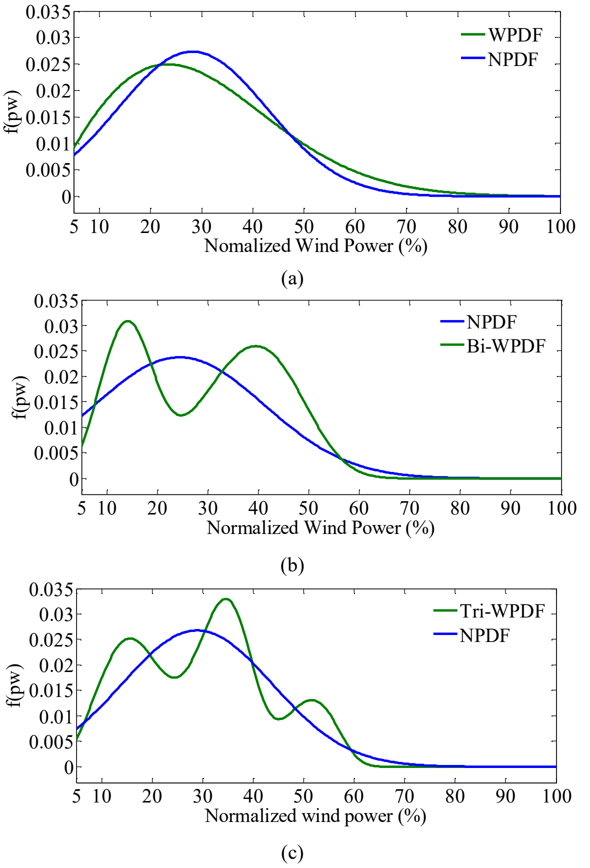

Fig. 1. Approximation WPDF to NPDF. (a) Single WPDF to NPDF. (b) bi-WPDF to NPDF. (c) tri-WPDF to NPDF

The NPDF derived is characterized by σ=14.6 and μ=28.2. In this case, the maximum error and percent of the forecast value error are 0.0042 and 6%, respectively.

B. Approximation of Bi-Weibull Distribution

If c=2, then the wind power distribution is bi-Weibull in which the parameters comprise: Γ_1=0.63, Γ_2=0.37, ρ_1=41.73, ρ_2=15.54, $\hbar_1$=4.55, $\hbar_2$=3.18. The approximation of the bi-Weibull to a specified NPDF is shown in Fig. 1(b). The resulting NPDF comprises σ=16.8 and μ=24.4. In this case, the maximum error and percent of the forecast value error are 0.0114 and 16.3%, respectively.

C. Approximation of Tri-Weibull Distribution

If c=3, then the wind power distribution is a tri-Weibull in which the parameters include: Γ_1=0.44, Γ_2=0.37, Γ_3=0.19, ρ_1=35.22, ρ_2=17.47, ρ_3=52.19, $\hbar_1$=6.86, $\hbar_2$=2.95, $\hbar_3$=9.73. The approximation of the tri-Weibull to a specified NPDF is shown in Fig. 1(c). The resulting NPDF comprises σ=14.9 and μ=28.9.

In this case, the maximum error and percent of the forecast value error are 0.0083 and 2.6%, respectively. By comparing the three approximations it can be observed that the approximation for a single Weibull and a tri-Weibull is better than a bi-Weibull. The maximum error is the maximum difference between the normal distribution and the Weibull distribution, while the forecast value error is obtained according to the mean definition of the probability distribution function.

IV. Linearization of Formulations

In the above formulation, several nonlinear terms are shown. These terms exist because of the production of continue variables and binary variables, e.g., (10), (20), (27) and (28).

Let r_i be the product of a bounded free variable y and set of binary variables m. The nonlinear terms in section II have the following form:

$$r_i = m_i \prod_{\substack{j=1 \\ j\neq i}}^{E} (1-A_j m_j) y \qquad \forall i \in I = (1,2,...,E) \tag{37}$$

where A_j is a parameter of forced outage rate, and E denotes the number of binary variables. Consequently, we can write:

$$r_i = m_i h \qquad \forall i \in I \tag{38}$$

$$h = \prod_{\substack{j=1 \\ j\neq i}}^{E} (1-A_j m_j) y \tag{39}$$

The term in (38) is expanded as follows:

$$h = y \times (1-A_1 m_1) \times (1-A_2 m_2) \times ... \times (1-A_E m_E) \tag{40}$$

Next, the following expressions are assumed:

$$W_j = W_{j-1} \times (1-A_j m_j) \qquad \forall j \neq i \tag{41}$$

$$h = W_E \tag{42}$$

In the first row in (41), W_1, is nonlinear since y is a variable and m_1 is a binary variable. The production of these two variables makes W_1 nonlinear. The equivalent linear form of W_1 can be given by:

$$y - m_1 Z \le W_1 \le y + m_1 Z \tag{43}$$

$$y(1-A_1) - (1-m_1)Z \le W_1 \le y(1-A_1) + (1-m_1)Z \tag{44}$$

where Z is a positive large enough constant and it should be greater than y. If m_1 equals zero, W_1 should be equal to y from (43) while the bounds in (44) are inactive. Otherwise, when m_1 equals one, W_1 from (44) should be equal to $y(1–A_1)$. Therefore, W_1 is converted to equivalent linear inequalities by (43)–(44). Then, we derive the linear form of W_j ($j \in I$–{1} and $i \in I$) which is formulated as:

$$W_j \le W_{j-1} + m_j Z \tag{45}$$

$$W_j \ge W_{j-1} - m_j Z \tag{46}$$

$$W_j \le W_{j-1}(1-A_j) + (1-m_j)Z \tag{47}$$

$$W_j \ge W_{j-1}(1-A_j) - (1-m_j)Z \tag{48}$$

According to (43)-(44), W_1 is either y or y $(1–A_1)$ wherein both cases, $0 \le W_1 \le y$. likewise, W_2 is either W_1 or $W_1(1–A_1)$. If m_j = 1, then W_j would be equal to $W_{j-1}(1–A_1)$ based on the inequalities (47) and (48) while inequalities (45) and (46) are inactive. If m_j = 0, the inequalities (45) and (46) state that W_j=W_{j-1} while the inequalities (47) and (48) do not bind. It is obvious that each W_j is a linear function of W_{j-1} and the expression associates to W_1 which is linear. Therefore, by (42)-(48), we can extract h as a linear function of binary variables m_i and continue variable y. Thus, the term r_i expressed in (38) can be linearized by the following equivalent linear inequalities:

$$-m_i Z \le r_i \le m_i Z \qquad \forall i \in I \tag{49}$$

$$W_E - (1-m_i)Z \le r_i \le W_E + (1-m_i)Z \qquad \forall i \in I \tag{50}$$

If x_i equals zero, r_i must be equal to zero from (49), while the bounds of (50) are inactive. Otherwise, if x_i equals one, r_i must be equal to W_E or h from (50), while the bounds of (49) are inactive. Finally, it should be noted that by linearizing equations such as (10) and (20) which have just one binary variable multiplying by a continuous variable, the procedure in (43) and (44) can be applied. Thus, the outcome becomes an integer linear programming (MILP) problem.

V. Case Studies

In this section, the proposed methodology is applied to BGTEP problem of IEEE 6-bus and IEEE 24-bus reliability test systems (RTS). All case studies are considered using CPLEX solver within GAMS [26] on a personal computer with Core i7 processor and 16 GB RAM.

A. 6-Bus Test System

The data for all components is founded in [27]. The planning horizon in this paper is one year. It is distributed to five sectors and for each sector a determined load factor. Multiplying the load factor of a sector at the annual peak load is defined as the load for each sector. Table I shows the load factor of each sector. The weight of the load is the ratio of the existing load at bus n to the total load. The weight of loads of buses 3, 4, 5 is 0.4, 0.3 and 0.3, respectively. Also, the value of VOLL is 1000$/MWh. In this section the case studies are addressed through two different approaches. In the first case it is assumed that RES in the system do not exist. In the second case it is assumed that wind turbines as RES can be added to the network.

1) Case A: Probabilistic BGTEP Model without the Effect of RES: In this case, the RES will be discarded and the only uncertain parameter is the load. Accordingly, the problem formulation without the wind is applied. The simulation results of BGTEP are shown in Table II. As can be seen, with an increasing annual peak load, the number of candidate components added to the network increases and thus it increases the value of the objective function. The simulation results show that the BGTEP model would be infeasible for the annual peak load equal to 80MW. This means that the system is not able to meet the demand of the network in the presence of new and existing components. The advantage of BGTEP when compared to GEP is less constructed units. In other words, through the use of new lines, BGTEP supplies the demand with a higher number of smaller generating units. Besides, it supplies the higher demand because the limitation of the lines doesn't allow the GEP to supply more load. Since the investment cost of the line is lower the new units and lines have no operation cost, it is concluded that the BGTEP is more effective economically.

2) Case B: Probabilistic BGTEP Model with the Effect of RES: In this case, the effect of RES is considered, and the problem formulation with the wind is used. In this case, the problem of wind power is its uncertainty. So, uncertainty is related to the load and wind power that can be expressed in the form of net demand power. Thus, according to the proposed method, the wind power should be described by a normal distribution which was discussed in detail in section III. Two wind turbines can be placed at buses 3, 4 and the capacity of each of them is 2.21 MW. The data of wind power in this paper is withdrawn from [28]. The simulation results of BGTEP is shown in Table III. In the presence of RES, the value of the objective function decreases. While part of the demand is met by wind turbines, the output power of generating units is reduced. The simulation results point out that the BGTEP model would be infeasible for an annual peak load equal to 85MW while this amount was 80 MW in the previous case. To clarify this issue, it can be considered a wind turbine placed on a special bus. Part of the load is supplied by wind power as a result of reduced power flow of the lines leading to the bus bar. The situation is similar to the one increased of capacity lines, thus more load is supplied. The simulation results point out that the value of the objective function for 60MW in case B is 12.786($10^6$$) while in case A is 14.342 ($10^6$$). Thus, the effect of wind is evident. The objective function versus reliability level is shown in Fig. 2 by the variation δ and ε for the annual peak load 50 MW. In the end, with an increased reliability level the value of the objective function increases. In fact, in order to have a higher reliability level more should be spent. Also, the variation of δ and ε affect the value of the objective function. In Fig. 2 with a different δ and ε the effect of reliability level on cost can be observed. It should be noted that the value of ε, δ, λ is 0.05 for all the results of the simulation.

TABLE I: DATA OF LOAD FACTOR FOR IEEE 6-BUS TEST SYSTEM

Time sector duration (h)	1510	2800	2720	1120	610
Load factor	0.5	0.65	0.8	0.9	1

TABLE II: RESULTS OF BGTEP WITHOUT RES

Annual peak load (MW)	New lines	New units	Number of new components	Cost ($10^6$$)
30	-	A4,A5,B4,B8	4	6.656
35	-	A5,B2,B3,B4,B8	5	7.604
40	-	A4,A5,B2,B3,B4, B7,B8	7	8.887
45	T2,T3	A1,A5,B1,B2, B3,B4,B7,B8	10	10.19
50	T2,T3	A1,A4,A5,B1,B2, B3,B4,B7,B8	13	11.550
55	T2,T3,T6,T7	A1,A4,A5,B2,B3, B4,B5,B7,B8	13	12.968
60	T2,T3,T6,T7	A1,A4,A5,B1,B2, B3,B4,B5,B7,B8	14	14.342
65	T2,T3,T6,T7	A1,A3,A4,A5,B1, B2,B3,B4,B5,B7, B8	15	15.870
70	T2,T3,T4,T6, T7	A1,A3,A4,A5,B1, B2,B3,B4,B5,B6, B7,B8	17	17.533
75	T2,T3,T4,T6, T7	A1,A3,A4,A5,B1, B2,B3,B4,B5,B6, B7,B8	17	19.207
80	Infeasible	Infeasible	Infeasible	Infeasible

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSTE.2018.2789398, IEEE Transactions on Sustainable Energy

TABLE III: RESULTS OF BGTEP WITH RES

Annual peak load (MW)	New lines	New units	Number of new components	Cost ($10^6$$)
30	-	A5,B3,B4,B8	4	5.230
35	-	A5,B2,B3,B4,B8	5	6.416
40	-	A5,B2,B3,B4,B7,B8	6	7.587
45	-	A4,A5,B2,B3,B4,B7,B8	7	8.687
50	T2,T3	A1,A4,A5,B2,B3,B4,B7,B8	10	9.987
55	T2,T3	A1,A4,A5,B1,B2,B3,B4,B7,B8	11	11.370
60	T2,T3,T6,T7	A1,A4,A5,B2,B3,B4,B5,B7,B8	13	12.786
65	T2,T3,T6,T7	A1,A4,A5,B1,B2,B3,B4,B5,B7,B8	14	14.140
70	T2,T3,T6,T7	A1,A3,A4,A5,B1,B2,B3,B4,B5,B7,B8	15	15.706
75	T2,T3,T4,T6,T7	A1,A3,A4,A5,B1,B2,B3,B4,B5,B6,B7,B8	17	17.377
80	T2,T3,T4,T6,T7	A1,A3,A4,A5,B1,B2,B3,B4,B5,B6,B7,B8	17	19.055
85	Infeasible	Infeasible	Infeasible	Infeasible

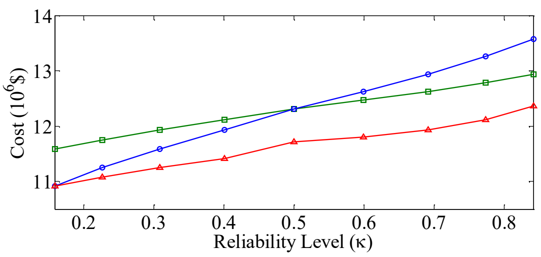

Fig. 2. Cost versus Reliability Level under different uncertainty levels and infeasibility tolerance

B. IEEE 24-Bus RTS

In this case study the existing generating units and lines are 32 and 38, respectively. The relevant data are available in [29], [30]. Table I is used for this test system, and the value of VOLL is 1000$/MWh. Due to the limitations in water resources, hydro units are not considered as candidate generators. The new lines are represented in Table IV, and relevant data is found in [31]. Also, the used capacity of wind turbines is 66.916 MW and placed at buses 1, 6, 9, 13, 16, 20.

This test system is simulated for both cases *A* and *B*. The simulation results are shown in Table V and Table VI. The effect of wind farms can be observed in the value of the objective function. For instance, the value of the objective function is 9.073 ($10^6$$) for 5000MW in case *A*, but this value is 6.554 ($10^6$$) in case *B*. So, in the presence of wind farms, in addition to reducing greenhouse gas emissions, operation costs will also be decreased. Table VII represents the run time of all simulations.

TABLE IV: NEW LINES FOR IEEE 24-BUS

New lines	(1-5),(3-9),(3-24),(4-9),(6-10),(7-8),(9-12) (10-12),(11-13),(12-13)

TABLE V: RESULTS OF BGTEP WITHOUT RES FOR IEEE 24-BUS RTS

Annual peak load (MW)	New lines	New units	Number of new components	Cost ($10^6$$)
4000	-	G2,G5,G6,G12,G14,G26	6	3.563
5000	T5	G1,G2,G5,G6,G12,G13,G14,G15,G17,G19,G22,G23,G26	14	9.073
6000	T5,T6	G1,G2,G3,G4,G5,G6,G7,G8,G9,G10,G11,G12,G13,G14,G21,G22,G23,G24,G25,G26	22	17.719

TABLE VI: RESULTS OF BGTEP WITH RES FOR IEEE 24-BUS RTS

Annual peak load (MW)	New lines	New units	Number of new components	Cost ($10^6$$)
4000	-	G5,G26	2	1.581
5000	-	G1,G2,G5,G6,G12,G13,G14,G23,G26	9	6.554
6000	T6	G1,G2,G5,G6,G7,G8,G10,G11,G12,G13,G14,G20,G22,G23,G24,G26	17	14.104

TABLE VII: THE RUN TIME OF SIMULATIONS

Case studies	6 bus without RES	6 bus with RES	24 bus without RES	24 bus with RES
Run time	1':20''	1':28''	5'':03'''	4'':37'''

VI. Conclusions

In this work, a new approach has been proposed which addresses the bundled generation and transmission planning under uncertainty based on a combination of robust and stochastic optimization strategies, which when applied to MILP problems produce "robust" solutions in the sense of being immune against wind generation and demand uncertainties. An unique feature of the proposed approach is that it can address many uncertain parameters in the BGTEP problem. Indeed, the approach can be applied to address the BGTEP problem with different uncertain resources. It should be noted that since the combination of RO and SP requires the uncertain variable to have a normal PDF, a new approximation methodology is proposed, which considers the Weibull PDF as a normal PDF with a minimum error. To validate the formulation, the variation of reliability levels under different uncertainty levels and infeasibility tolerance have been studied in the test networks. Also, the linearization of the formulation provided a lower complexity in the simulation results. Besides, the effect of contingency and reliability on the BGTEP problem has been considered.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSTE.2018.2789398, IEEE Transactions on Sustainable Energy

The computational results show that this approach provides an effective way to address planning problems under uncertainty, producing reliable schedules and generating helpful insights on tradeoffs between conflicting objectives. Accordingly, due to the efficient and easy to handle formulation, the approach is capable of solving real-world problems with a large number of uncertain parameters.

APPENDIX

In this section the proposed method is proven. The problem based on combination RO and SP is expressed as follows [21]:

$$\min/\max \quad q^T x + j^T y \tag{51}$$

$$Gx + Dy \le e \tag{52}$$

$$\sum_m g_{lm} x_m + \sum_i d_{li} y_i + \varepsilon\lambda \sqrt{\sum_{m\in M_l} g_{lm}{}^2 x_m{}^2 + \sum_{i\in I_l} d_{li}{}^2 y_i + e_l^2} \le e_l + \delta \max[1, |e_l|] \quad \forall l \tag{53}$$

$$\underline{x} \le x \le \overline{x} \tag{54}$$

$$y_i = 0,1 \qquad \forall i \tag{55}$$

$$g_{lm}^{true} = (1 + \varepsilon\xi_{lm}) g_{lm} \tag{56}$$

$$d_{li}^{true} = (1 + \varepsilon\xi_{li}) d_{li} \tag{57}$$

$$e_l^{true} = (1 + \varepsilon\xi_l) e_l \tag{58}$$

Also, constraints (13), (14), (16) are considered. In the above MILP problem, G and D are uncertain parameters while x and y are variables. M_l and I_l are the set of indices regarding uncertain parameters. Constraints (56)-(58) denote the relation between true value and nominal value. In order to prove this problem, two conditions must be established:

(i) the problem is feasible for the nominal value;

(ii) $\Pr\left\{ \sum_m g_{lm}^{true} x_m + \sum_i d_{li}^{true} y_i > e_l^{true} + \delta \max[1, |e_l|] \right\} \le \kappa$

where $\lambda = F_n^{-1}(1-\kappa)$.

Proof of condition (ii):

$$\Pr\left\{ \sum_m g_{lm}^{true} x_m + \sum_i d_{li}^{true} y_i > e_l^{true} + \delta \max[1, |e_l|] \right\}$$

$$= \Pr\left\{ \begin{array}{l} \sum_m g_{lm} x_m + \varepsilon \sum_{m\in M_l} \xi_{lm} |g_{lm}| x_m + \sum_i d_{li} y_i + \varepsilon \sum_{i\in I_l} \xi_{li} |d_{li}| y_i > \\ e_l + \varepsilon\xi_l |e_l| + \delta \max[1, |e_l|] \end{array} \right\}$$

$$\le \Pr\left\{ \begin{array}{l} (\sum_{m\in M_l} \xi_{lm} |g_{lm}| x_m + \sum_{i\in I_l} \xi_{li} |d_{li}| y_i - \xi_l |e_l|) \\ / \sqrt{\sum_{m\in M_l} g_{lm}{}^2 x_m{}^2 + \sum_{i\in I_l} d_{li}{}^2 y_i + e_l^2} > \lambda \end{array} \right\}$$

$$= 1 - \Pr\left\{ \begin{array}{l} (\sum_{m\in M_l} \xi_{lm} |g_{lm}| x_m + \sum_{i\in I_l} \xi_{li} |d_{li}| y_i - \xi_l |e_l|) \\ / \sqrt{\sum_{m\in M_l} g_{lm}{}^2 x_m{}^2 + \sum_{i\in I_l} d_{li}{}^2 y_i + e_l^2} \le \lambda \end{array} \right\}$$

$$= 1 - F_n(\lambda) = 1 - (1-\kappa) = \kappa$$

where $\dfrac{(\sum_{m\in M_l} \xi_{lm} |g_{lm}| x_m + \sum_{i\in I_l} \xi_{li} |d_{li}| y_i - \xi_l |e_l|)}{\sqrt{\sum_{m\in M_l} g_{lm}{}^2 x_m{}^2 + \sum_{i\in I_l} d_{li}{}^2 y_i + e_l^2}}$ is a random variable with standardized normal distribution.

As seen in the appendix and in [20] and [21] the wind distribution approximation is not applied in the formulation but is used to prove the proposed method.

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