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A Congestion Management Approach Using Probabilistic Power Flow Considering Direct Electricity Purchase

Xu Wang* and Chuan-Wen Jiang†

Abstract – In a deregulated electricity market, congestion of the transmission lines is a major problem the independent system operator (ISO) would face. Rescheduling of generators is one of the most practiced techniques to alleviate the congestion. However, not all generators in the system operate deterministically and independently, especially wind power generators (WTGs). Therefore, a novel optimal rescheduling model for congestion management that accounts for the uncertain and correlated power sources and loads is proposed. A probabilistic power flow (PPF) model based on 2m+1 point estimate method (PEM) is used to simulate the performance of uncertain and correlated input random variables. In addition, the impact of direct electricity purchase contracts on the congestion management has also been studied. This paper uses artificial bee colony (ABC) algorithm to solve the complex optimization problem. The proposed algorithm is tested on modified IEEE 30-bus system and IEEE 57-bus system to demonstrate the impacts of the uncertainties and correlations of the input random variables and the direct electricity purchase contracts on the congestion management. Both pool and nodal pricing model are also discussed.

Keywords: PPF, Congestion Management, ABC, 2m+1 PEM, Direct electricity purchase

1. Introduction

Congestion of transmission lines occurs when the networks fail to accommodate all the desired transactions due to the system operating limits such as branch power flow limits, voltage limits, etc. Congestion in one or more transmission lines leads to higher risk of electricity consumption, even unexpected widespread power blackouts [1]. Various congestion management approaches suitable for traditional power systems without intermittent energy, have been reported in recent literatures. However, the global rapid growth of wind power capacity increases the uncertainties in congestion management. Therefore, it is necessary to propose an efficient and reliable method to process congestion problem with random variables.

Optimal rescheduling of generators is generally adopted to manage the congestion for its low-cost and simplicity. Ashwani Kumar proposed a zonal sensitivity-based optimum real and reactive power generation rescheduling method for congestion management [2]. Another technique for optimum selection of generators to be rescheduled is demonstrated in [3], which is based on generator sensitivities to the power flow on congested lines. Congestion management techniques in different deregulated electricity markets are estimated in [4]. Besides, congestion management scheme based on optimal power flow (OPF) is an excellent alternative method in a power system with deterministic operational constraints.

An OPF-based congestion management approach proposed in [5] is based on the nodal pricing framework and the pool model. Another OPF-based scheme which aims to minimize both congestion and service costs is presented in [6]. Various kinds of traditional congestion management models are essentially the OPF problems associated with security constraints. As system with high level wind power integration has enhanced uncertainties, a noval probabilistic OPF-based congestion management approach is addressed in this paper.

Cumulants and Gram-Charlier expansion theory are combined to approximate the probabilistic distribution functions (PDFs) of transmission line flows in [7]. As the cumulant method can't be used to process correlated input random variables, a two PEM [8] is applied. Literature [9] reveals that the 2m+1 PEM provides the best performance among the Hong's PEMs. So this paper uses the 2m+1 PEM [9-10] to process the PPF in the congestion management. In recent years, compared with other heuristic mothods [11-14], ABC algorithm proposed by D. Karaboga [11] for fewer parameters, faster convergence and higher precision [12] has been widely used to solve complex nonlinear optimization problems, such as congestion management [13], OPF [14], etc.

Congestion management methods available in most literatures use simple power flow method without considering the uncertainties and correlations of the input variables. In this paper, the ABC algorithm combined with an extended 2m+1 PEM method is proposed to

† Corresponding Author: Dept. of Electrical Engineering, Shanghai Jiao Tong University, China. (jiangcw@sjtu.edu.cn)
* Dept. of Electrical Engineering, Shanghai Jiao Tong University, China. (wangx198912@163.com)
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process the complex congestion problem with correlated random injections. Moreover, the impact of direct electricity purchase on the results of congestion is discussed.

This paper is organized as follows. The mathematical formulation of the congestion management model is presented in Section 2. Section 3 gives the PPF model coupled with correlated variables in detail. In Section 4, the ABC algorithm coupling with the PPF model to solve the complex congestion problem is proposed. Section 5 gives several case studies. Finally, Section 6 provides the relevant conclusions.

2. Mathematical Formulation

Congestion management is an optimization problem aims to minimize the congestion cost while satisfying the system and unit constraints. This section gives the congestion management model based on both pool and nodal pricing model in detail.

2.1 Objective functions

2.1.1 Cost of rescheduling in the pool model [15-16]

In the pool model, the ISO determines the market-clearing price $C_{i,M}$ and the output P_{Gi} of generator i without considering system constraints aiming to minimize the cost of electricity purchase. The original total cost of electricity purchase can be calculated by:

$$C_{org} = \sum_{i=1}^{N_G} P_{G_i} C_{i,M} \tag{1}$$

where N_G is the number of generators. When the congestion occurs, the cost of "constraint on" and "constraint off" generators are:

$$\begin{aligned} C_{on} &= \sum_{i=1}^{N_G^{on}} (P'_{G_i} - P_{G_i}) C'_{i,M}(P'_{G_i}) + \sum_{i=1}^{N_G^{on}} P_{G_i} C_{i,M} \\ C_{off} &= \sum_{i=1}^{N_G^{off}} (P_{G_i} - P'_{G_i})(C_{i,M} - C'_{i,M}(P'_{G_i})) + \sum_{i=1}^{N_G^{off}} P'_{G_i} C_{i,M} \end{aligned} \tag{2}$$

where N_G^{on} and N_G^{off} are the number of "constraint on" and "constraint off" generators, respectively; P'_{G_i} is the output of generator *i* after rescheduling; $C'_{i,M}$ is the actual price bids submitted by generator *i*. Combining (1-2), the cost of rescheduling in the pool model is obtained:

$$C_1 = \overline{C}_{on} + \overline{C}_{off} - C_{org} \tag{3}$$

In the above formula, the superscript '$-$' denotes the expectation of the random variables.

2.1.2 Cost of breach of direct electricity purchase contract

Actually, the direct electricity purchase contract is a kind of bilateral transactions [16]. If there is no static and dynamic security violation, all the requested contracts or transactions should be satisfied. Otherwise, a breach of contract will occur. Mathematically, the breach cost of a direct electricity purchase contract at generator *i* can be calculated according to [16] as follows:

$$C_2 = \begin{cases} (P_{i,dc} - P'_i) \cdot k \cdot C'_{i,M}(P'_i), P_{i,dc} > P'_i \\ 0, \quad P_{i,dc} \le P'_i \end{cases} \tag{4}$$

where $P_{i,dc}$ is the trading power of the direct electricity purchase contract of generator *i*, P'_i is the actual active power of generation *i*, and *k* is a penalty coefficient of breach of contract.

2.1.3 Congestion cost in different modes

Combining (3-4), the objective function in the pool mode is:

$$\text{Minimize } f_1 = C_1 + wC_2 \tag{5}$$

where *w* is a penalty coefficient trying to perform all the direct electricity purchase contracts.

Though the formula (4) is still applicable in the nodal pricing model [5], the objective function is modified to:

$$\text{Minimize } f_2 = \sum_{(i,j)\in S} \left| (LMP_i - LMP_j) \cdot P_{ij} \right| + wC_2 \tag{6}$$

where *S* is the set of the two endpoints of the branches; P_{ij} is the active power flow from bus *i* to *j*; LMPi and LMP_j is the nodal prices of bus *i* and *j*, which are two endpoints of a branch, respectively. All the nodal prices are calculated by minmizing the cost of generation.

2.2 Constrains and limits

2.2.1 Power flow equations

$$\begin{cases} P_i = V_i \sum_{j=1}^{N_{bus}} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \\ Q_i = V_i \sum_{j=1}^{N_{bus}} V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) \end{cases} \tag{7}$$

where P_i, Q_i and V_i are the active power, reactive power and voltage amplitude of bus *i*, respectively; *Gij* and *Bij* are conductance and susceptance between bus *i* and *j*, respectively; N_{bus} is the number of buses; θ_{ij} is the phase angle difference between bus *i* and *j*.

2.2.2 Power constraints of generators

$$\begin{cases} P_{G_i}^{min} \le P_{G_i} \le P_{G_i}^{max} \\ Q_{G_i}^{min} \le Q_{G_i} \le Q_{G_i}^{max} \end{cases}, i = 1,2,\ldots,N_G \tag{8}$$

where $P_{G_i}^{min}$ and $P_{G_i}^{max}$ are the minimum and maximum active power of generator i; $Q_{G_i}^{min}$ and $Q_{G_i}^{max}$ are the minimum and maximum reactive power of generator i; P_{Gi} and Q_{Gi} are the active and reactive power of generator i.

2.2.3 Bus voltage limits

$$Pro(V_i^{min} \le V_i \le V_i^{max}) \ge \alpha_i, i = 1,2,\ldots,N_{bus} \tag{9}$$

where $Pro(\cdot)$ denotes the probability of the event $(\cdot)$; V_i^{min} and V_i^{max} are the lower and upper bound of voltage amplitude of bus i; V_i is the voltage amplitude of bus i; α_i is the confidence level of the bus i's constraint.

2.2.4 Line power flow limits

$$Pro(|PF_i| \le PF_i^{max}) \ge \beta_i, \quad i = 1,2,\ldots,N_{branch} \tag{10}$$

where PF_i^{max} are the upper limit of transmission power flow of branch i; PF_i is the power flow of branch i; β_i is the confidence level of the branch i's constraint; N_{branch} is the number of the branches.

2.2.5 Direct electricity purchase contract

In a practical system, not all of the generators have direct electricity purchase contract with loads and vice-versa. Mathematically, if a generator at bus i have this contract the active power inequality constraint of (8) is modified into:

$$max\{P_{G_i}^{min}, P_{i,dc}\} \le P_{G_i} \le P_{G_i}^{max} \tag{11}$$

For the objective function has already considered the penalty term of this constraint violation, only constraint (8) need to be taken into account.

3. PPF Model Managing To Process Correlations

To perform the impact of the uncertainties of loads and wind farms (WFs), probabilistic models are established. Since the correlations among loads and WFs do affect the power flows [17], a modified 2m+1 PEM [10] capable of processing the correlations is introduced.

3.1 Probabilistic load model

Generally, load demand is supposed to follow a normal distribution [10, 17]. So the active and reactive power of load bus L can be expressed by:

$$\begin{aligned} f(P_L) &= \frac{1}{\sqrt{2\pi}\sigma_{P_L}} \exp\left(\frac{(P_L - \mu_{P_L})^2}{2\sigma_{P_L}^2} \right) \\ f(Q_L) &= \frac{1}{\sqrt{2\pi}\sigma_{Q_L}} \exp\left(\frac{(Q_L - \mu_{Q_L})^2}{2\sigma_{Q_L}^2} \right) \end{aligned} \tag{12}$$

where μ_{P_L} and σ_{P_L} are the mean and standard deviation of active load; μ_{Q_L} and σ_{Q_L} are the mean and standard deviation of reactive load; $\exp(\cdot)$ represents the exponential function.

3.2 Probabilistic correlated WFs model

Different from the probabilistic load model, the output of WFs depends on the wind speed which follows the Weibull distribution. Thus, the joint PDF of the correlated WFs' output at bus t can be obtained through the correlated wind speed using Monte Carlo method.

The PDF and cumulative distribution function (CDF) of the wind speed v_j of the j-th WF at bus t are as follows [10]:

$$\begin{aligned} f_j(v_j) &= \frac{k_j}{\lambda_j}\left(\frac{v_j}{\lambda_j}\right)^{k_j - 1} e^{-(v_j/\lambda_j)^{k_j}} \quad v_j \ge 0 \\ F_j(v_j) &= 1 - e^{-(v_j/\lambda_j)^{k_j}} \quad v_j \ge 0 \end{aligned} \tag{13}$$

where k_j is the shape factor and λ_j is the scale factor of v_j. Weibull distributed wind speed can be transformed into normally distributed variable through Nataf transformation.

The correlated wind speed sampling matrix $V_{N_s \times N_{WFs,t}} = [v_1, v_2, \cdots, v_{N_{WFs,t}}]$ (N_s represents the sampling times) of the $N_{WFs,t}$ WFs at bus t can be generated as follows:

1. Generate a matrix $R_{N_s \times N_{WFs,t}} = [r_1, r_2, \cdots, r_{N_{WF,t}}]$ by the Matlab random number generator which represents $N_{WFs,t}$ independent standard normal distributed random variables.
2. For the given correlation coefficient matrix C_g of the wind speeds, the modified correlation coefficient matrix C_{md} by the Nataf transformation [19] are obtained using [10, 20]:

$$\rho'_{mn} = G\rho_{mn} \tag{14}$$

$$\begin{aligned} G = {} & 1.063 - 0.004\rho_{mn} - 0.2(\gamma_m + \gamma_n) - 0.001\rho_{mn}^2 \\ & +0.337(\gamma_m^2 + \gamma_n^2) + 0.007\rho_{mn}(\gamma_m + \gamma_n) - 0.007\gamma_m\gamma_n \end{aligned} \tag{15}$$

where and ρ'_{mn} are the elements at m-th row, n-th column of C_g and C_{md}, respectively; γ_m and γ_n are the coefficients of variation of v_m and v_n. Then decompose C_{md} by the Cholesky decomposition method [10, 21] into $C_m = LL^T$, where L is an inferior triangular matrix.

3. Using the transformation $Y=LR$ and the inverse Nataf transformation $v_j = F_j^{-1}(\Phi(Y))$, we can obtain the matrix $V_{N_s \times N_{WFs,t}} = [v_1, v_2, \cdots, v_{N_{WFs,t}}]$ with $N_{WFs,t}$ Weibull distributed variables with a correlation coefficient matrix C_d.

Next, the wind speed vector v_j from the j-th column of V is used to determine the output column vector $P_{WF,j}$ $[N_s \times 1]$ of WF j with n_j WTGs at the bus t as follows:

$$P_{WF,j}(v_j) = \begin{cases} 0 & v_j < v_{in} \\ n_j P_r (v_j - v_{in}) / (v_r - v_{in}) & v_{in} \le v_j \le v_r \\ n_j P_r & v_r < v_j \le v_{out} \\ 0 & v_j > v_{out} \end{cases} \quad (16)$$

where P_r is the rated power of a single WTG; v_{in}, v_r and v_{out} are the cut-in, rated and cut-out wind speed, respectively; n_j is the number of WTGs at the bus t.

Applying V and (16), the output sampling matrix P_{WFs} $[N_s \times 1]$ of bus t with $N_{WFs,t}$ WFs is calculated by:

$$P_{WFs} = \sum_{j=1}^{N_{WFs,t}} P_{WF,j} \quad (17)$$

Using P_{WFs}, the mean $\mu_{WFs,t}$ and standard deviation $\sigma_{WFs,t}$ of the WFs' output at bus t can be obtained:

$$\begin{cases} \mu_{WFs,t} = \dfrac{1}{N_s} \displaystyle\sum_{i=1}^{N_s} P_{WFs}(i) \\ \sigma_{WFs,t} = \sqrt{\dfrac{1}{N_s} \displaystyle\sum_{i=1}^{N_s} \left[P_{WFs}(i) - \mu_{WFs,t} \right]^2} \end{cases} \quad (18)$$

where $P_{WFs}(i)$ is the i-th element of P_{WFs}. The z-th ($z>2$) order standardized central moments of the bus t with WFs can be calculated as:

$$M_{z,t} = \left(\frac{1}{N_s} \sum_{i=1}^{N_s} \left[P_{WFs}(i) - \mu_{WFs,t} \right]^z \right) \Big/ \sigma_{WFs,t}^z \quad (19)$$

So far, probabilistic models of loads and WFs have been established. No matter the random injections are continuous or discrete, the traditional 2m+1 PEM can be just applied to uncorrelated ones. Thus, Part C introduces a modified 2m+1 PEM capable of dealing with correlated random injections at each bus.

3.3 2m+1 PEM for correlated random variables

As mentioned above, independent input random variables are required in the 2m+1 PEM proposed in [9, 10]. For this purpose, the orthogonal transformation [10] based on Cholesky decomposition method [21] is used. A detailed description of the orthogonal transformation is given in [10], which can convert a set of correlated input variables into an uncorrelated one. Based on the principle of the 2m+1 PEM [10], processing the correlations of the input random variables is to process the correlations of their standardized central moments. The 2m+1 PEM for correlated input random variable is as follows:

Step 1. According to the correlation coefficient matrix of the input random variables $p=[p_1, p_2, \ldots, p_m]^T$, obtain the variance-covariance matrix C_p. Then get the matrix B by the Cholesky decomposition method using $C_p=LL^T$ and $B=L^{-1}$.

Step 2. Transform the correlated input variables p into a new set of independent variables $q=[q_1, q_2, \ldots, q_m]^T$ whose first four central moments satisfy:

$$\begin{aligned} &\mu_q = B\mu_p; \\ &\sigma_q = I_m; \\ &\lambda_{q_l,j} = \sum_{i=1}^{m} (b_{li})^j \lambda_{p_i,j} \sigma_{p_i}^j, l=1,2,\ldots,m; j=3,4. \end{aligned} \quad (20)$$

where μ_p and μ_q are the mean vectors of p and q; σ_p and σ_q are the standard deviation vectors of p and q; I_m is the m-dimensional identity matrix; $\lambda_{q_l,j}$ (j=3,4) are the coefficients of skewness and kurtosis of q_l; b_{li} is the element at the l-th row, i-th column of B.

Step 3. Calculate the new transformed pairs ($q_{l,k}$, $\omega_{l,k}$) of independent q defining the new 2m+1 PEM using follows:

$$q_{l,k} = \mu_{q_l} + \xi_{l,k} \cdot \sigma_{q_l}, \quad k=1,2,3 \quad (21)$$

$$\begin{cases} \omega_{l,k} = \dfrac{(-1)^{3-k}}{\xi_{l,k}(\xi_{l,1} - \xi_{l,2})}, \quad k=1,2 \\ \omega_{l,3} = \dfrac{1}{m} - \dfrac{1}{\lambda_{l,4} - \lambda_{l,3}^2} \end{cases} \quad (22)$$

where $\xi_{l,k}$ can be calculated by:

$$\begin{aligned} &\xi_{l,k} = \frac{\lambda_{q_l,3}}{2} + (-1)^{3-k} \sqrt{\lambda_{q_l,4} - \frac{3}{4}\lambda_{q_l,3}^2}, \quad k=1,2 \\ &\xi_{l,3} = 0 \end{aligned} \quad (23)$$

Step 4. Construct the new 2m+1 points in the form $(\mu_{q_1}, \cdots, q_{l,k}, \cdots, \mu_{q_m}), k=1,2$ and $(\mu_{q_1}, \cdots, \mu_{q_l}, \cdots, \mu_{q_m})$. Let $q_{2m+1,k}$, k=1, 2, 3, be a $m \times m$ matrix each row of which is one point of the 2m+1 points with l from 1 to m. Then transform the 2m+1 points to the original space using $p_{2m+1,k}=B^{-1}q_{2m+1,k}$.

Step 5. Calculate the deterministic power flow for each row of $p_{2m+1,k}$ for 2m+1 times using:

$$s_i(l,k) = Z_i(\mu_{p_1}, \mu_{p_2}, \cdots, p_{l,k}, \cdots, \mu_{p_m}), \quad \begin{matrix} l=1,2,\cdots m \\ k=1,2 \end{matrix} \quad (24)$$

The solution vectors $s_i(l, k)$ is obtained.

Step 6. Estimate the the j-th raw moment using:

$$E(s_i^j) \approx \sum_{k=1}^{2}\sum_{l=1}^{m}\left[\omega_{l,k}\cdot\left(s_i(l,k)\right)^j\right] + [Z_i(\mu_{p_1},\mu_{p_2},\cdots,\mu_{p_m})]^j\cdot\sum_{l=1}^{m}\omega_{l,3},\quad j=1,2,\cdots \tag{25}$$

And the PDF and CDF of the output random variable s_i can be calculated through Gram-Charlier expansion [7, 16]:

$$\begin{aligned} h_i(S_i) &= \varphi(S_i)+\frac{c_1}{1!}\varphi'(S_i)+\cdots+\frac{c_6}{6!}\varphi^{(6)}(S_i) \\ H(S_i) &= \Phi(S_i)+\frac{c_1}{1!}\Phi'(S_i)+\cdots+\frac{c_6}{6!}\Phi^{(6)}(S_i) \\ S_i &= \frac{s_i-\mu_{s_i}}{\sigma_{s_i}} \end{aligned} \tag{26}$$

where $\varphi(\cdot)$ and $\Phi(\cdot)$ are the PDF and CDF of standard normal distribution, respectively; c_i are constant coefficients of which detailed calculation can refer to [7, 16]; μ_{s_i} and σ_{s_i} are the mean and standard deviation of s_i.

4. Solution Method

A PPF model capable of managing correlated random injections has been described in the previous section to simulate the uncertainties and correlations in a congestion management problem. This section will give a detailed introduction of the ABC algorithm coupling with the PPF model to solve the complex congestion model.

4.1 Overview of the ABC algorithm

Initially, the ABC algorithm is proposed for optimizing numerical unconstrained problems, which is a swarm-based meta-heuristic algorithm [22]. Then it is modified in [23] to handle constrained optimization problems.

In the ABC algorithm, every food source represents a possible solution of an optimization problem, and nectar amount of a food source represents the fitness of the corresponding food source. The process of artificial bees' searching for the best food source is the optimization process. The colony of artificial bees includes three groups of bees: employed bees, onlookers and scout bees. The search of food source implemented by the artificial bees can be summarized as following:

1. Employed bees find the food source within the neighborhood of the previous food source in their memory and record the nectar amount of the new food source.
2. According to the information offered by the employed bees, onlookers judge the merits of the food source and select a food source probabilistically.
3. Employed bee at abandoned inferior food source becomes a scout bee and starts search a new food source randomly.

The main steps of the ABC algorithm are as follows:

Step 1. Initialize the randomly distributed food-source positions X_i=[$x_{i,1}$, $x_{i,2}$, …, $x_{i,d}$] (solutions population) according to the upper and lower limits of the decision variables, where i=1,2,…,N (N represents the number of employed bees, onlooker bees and food sources), $x_{i,j}$ (j=1,2,…,d) represents the j-th decision variable of the solution X_i and d is the number of decision variables.

Step 2. Compute the nectar amount of the food source X_i using their fitness values:

$$Fitness_i = \begin{cases} \dfrac{100}{1+f}, & f\ge 0 \\ 100+|f|, & f<0 \end{cases} \tag{27}$$

where f is the objective function value at solution X_i.

Step 3. Determine neighborhood positions for the employed bees according to the exiting food-source positions using:

$$x_{i,j}^{new} = x_{i,j}^{old} + U(x_{i,j}^{old} - x_{k,j}) \tag{28}$$

where $x_{i,j}$ is the j-th parameter of solution X_i that was selected to be modified; U is a random number between [-1,1]; $k\ne i$ and $k\in\{1,2,\ldots,N\}$; $i\in\{1,2,\ldots,N\}$; $j\in\{1,2,\ldots,d\}$. Then record the fitness values of the new neighborhood positions using (27).

Step 4. If the fitness value of a new neighborhood position is larger than the old one, replace the old one with the new one; otherwise, keep the old one.

Step 5. Calculate the selection probability $Prob_i$ of the solution X_i for the outlook bees applying:

$$Prob_i = 0.9\times\frac{Fitness_i}{Fitness_{max}}+0.1, i=1,2,\ldots,N \tag{29}$$

Step 6. Select the onlooker bee depending on the probability value. For the selected onlooker bee Xi, a new neighborhood position is created using (28); else go to Step 8. Then record the fitness values of the new neighborhood positions using (27).

Step 7. Follow the Step 4.

Step 8. Find the abandoned food sources for scout bees. If a food source is still not updated by a predetermined number of trials known as 'limit' value Lim_{max} , then that food source is abandoned and the corresponding employed bee becomes a scout. Otherwise, no abandoned food sources exist and go to Step 10.

Step 9. For an abandoned food source X_i, update it with a completely new food source V_i through:

$$v_{i,j} = x_i^{min} + u_j(x_i^{max} - x_i^{min}), j = 1,2,\ldots,d \tag{30}$$

where u_i is a random number between [0,1]; x_i^{max} and x_i^{min} are the maximum and minimum parameter of X_i, respectively.

Step 10. Storage the global best solution obtained so far.

Step 11. If the current iteration number (*Iter*) is larger than the maximum iteration number of the search process ($Iter_{max}$), stop and output the results. Otherwise, go back to Step 3.

There are three control parameters need to be set: 1) food-source size N, representing the number of employed bees or onlooker bees; 2) 'limit' value, which is the number of trials determining a food-source position abandoned or not (at least $0.5 \times N \times d$ suggested in [11]); 3) $Iter_{max}$, that is the maximum iteration number.

4.2 Congestion management strategy

After alleviating congestion in transmission grids, the congestion may occur again due to the uncertainties and correlations of loads and wind power. Moreover, direct electricity purchase contracts affect the rescheduling of generators obviously. In case of congestion again, all the generators participating in congestion management must be rescheduling properly. This paper proposes a congestion management approach using PPF considering direct electricity purchase. If congestion cannot be removed just by rescheduling, a breach of contract is done between contracted parties based on its liquidated damage.

This paper uses the following methods to handle the constraints (7-10). Mathematically, equality constraint (7) is solved during the determined power flow calculation. Inequality constraint (8) can be handled as follows:

if $P_{G_i} < P_{G_i}^{min}$, $P_{G_i} = P_{G_i}^{min}$;

if $P_{G_i} > P_{G_i}^{max}$, $P_{G_i} = P_{G_i}^{max}$.

Reactive power constraints of generators are processed by the similar method. Besides, if reactive power generation of any PV bus gets violated, the PV bus is treated as PQ bus.

The chance constraints (9) and (10) are handled as follows:

4.2.1 Calculate the penalty terms:

$$\begin{aligned} Pen\_V &= \sum_{i=1}^{N_{bus}} \left| \frac{\Delta V_i}{V_i^{max} - V_i^{min}} \right| \\ Pen\_P &= \sum_{i=1}^{N_{line}} \left| \frac{\Delta P_i}{P_i^{max}} \right| \end{aligned} \tag{31}$$

where Pen_V and Pen_P are the penalty terms of bus voltage limits and line power flow limits; ΔV_i and ΔP_i are computed by:

$$\Delta V_i = \begin{cases} 0, & (9)\ satisfied \\ max\left\{V_i^{min} - V_i^{down}, V_i^{up} - V_i^{max}\right\}, & else \end{cases} \tag{32}$$

$$\Delta P_i = \begin{cases} 0, & (10)\ satisfied \\ P_i^{up} - P_i^{\max}, & else \end{cases} \tag{33}$$

where $Pro(V_i<V_i^{down}) = 1-\alpha_i$, $Pro(V_i>V_i^{up}) = 1-\alpha_i$, and $Pro(|P_i|>P_i^{up}) = 1-\beta_i$.

4.2.2 Modify the original objective function f into:

$$f_{new} = f + w_V Pen\_V + w_P Pen\_P \tag{34}$$

where w_V and w_P are the penalty factors.

4.3 ABC algorithm coupling with PPF model

ABC algorithm coupling with PPF model is proposed to solve the congestion management problem with correlated random injections. The flowchart of the proposed

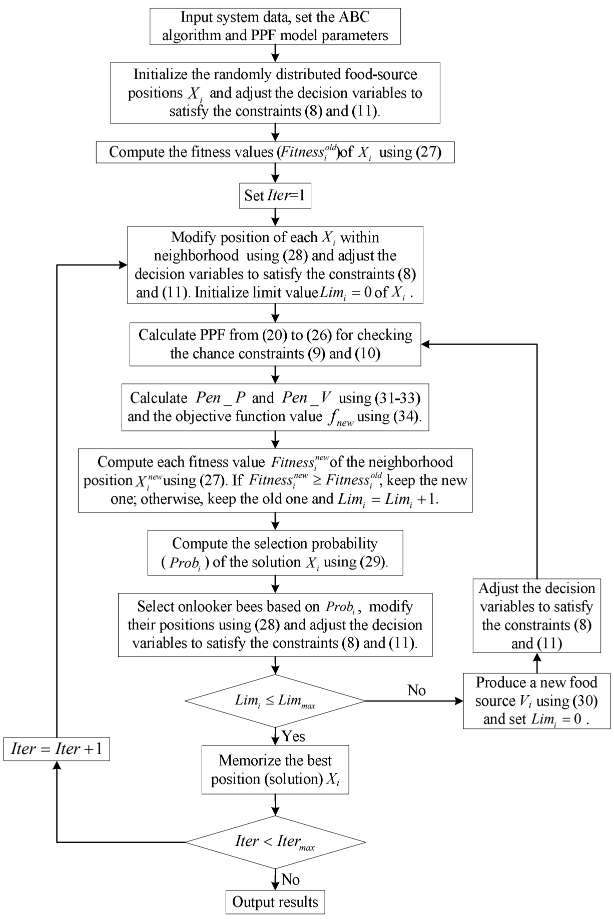

Fig. 1. Flowchart for the ABC algorithm coupling with PPF

ABC algorithm is illustrated in Fig. 1. Further studies in [22-28] has proved that the ABC algorithm has a better performance in results and solutions compared with other popular population-based and heuristic optimization algorithms.

5. System Studies

The proposed congestion management approach has been illustrated on the modified IEEE 30-bus test system [29-30] and IEEE 57-bus test system [31] in the pool model in 5.1 and 5.2. The performance of the ABC algorithm is compared with that of evolutionary algorithm (EA) [32] and particle swarm optimization (PSO) [32] in 5.1. Similar study of IEEE 30-bus is conducted in nodal pricing model in 5.3. All the studies are implemented in MATLAB 2012a.

5.1 Modified IEEE 30-bus case study

The modified IEEE 30-bus test system consists of 6 generators (Table 1), 41 branches, 20 load buses whose data are from Table 2-3 of [30], and 2 WFs located at bus 28 as shown in Fig. 2. The active power consumption of each load is considered to be normally distributed with means equal to the values provided in Table 3 of [30] with the value at bus 5 zeroed out, and standard deviations of 10% with respect to such mean values. For simplicity, the power factor of each load is kept constant. Each WF

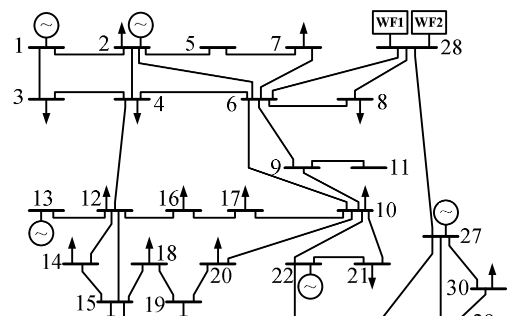

Fig.2. Modified IEEE 30-bus test system

Table 1. Generator data for modified 30-bus system

Bus No.	P_{max} [MW]	P_{min} [MW]	Q_{max} [MW]	Q_{min} [MW]	Bidding coefficients	
					a	b
1	200	50	250	-20	0.0075	2.00
2	80	20	100	-20	0.035	1.75
3	40	12	60	-15	0.05	3.00
22	50	15	80	-15	0.125	1.00
23	30	10	50	-10	0.05	3.00
27	35	10	80	-15	0.01668	3.25

Bidding function: $f_B(P)$= a P + b \$/MWh

Table 2. Probable congested line details of 30-bus system with different r_L (Line limit 32MVA)

r_L	Probable Congested Line	Expected Power Flow [MVA]	Standard Deviation [MVA]	Congestion Probability [p. u.]
0	6-8	34.7745	3.7584	0.7788
0.2	6-8	34.7752	3.7982	0.7724
0.4	6-8	34.7758	3.8376	0.7761
0.5	6-8	34.7762	3.8571	0.7662
0.6	6-8	34.7765	3.8766	0.7695
0.8	6-8	34.7772	3.9105	0.7771
	21-22	26.8959	2.4617	0.0147
0.9	6-8	34.7775	3.9340	0.7337
	21-22	26.9009	2.5558	0.0308

Table 3. Comparison results of different algorithms

Method	Congestion cost [\$/h]	Expected power flow [MVA]	
		line 6-8	Line 6-28
ABC	11.7253	33.7879	11.1362
EA	12.6368	33.7889	11.5247
PSO	12.2429	33.7878	11.4813

contains five 3MW WTGs and the wind speed is assumed to follow the Weibull distribution with scale and shape parameters 9, 2.205, respectively. Both WFs are correlated with a correlation coefficient 0.9 and a power factor 0.9 lag. Besides, the involved parameters are set as follows: w_V=10^6, w_P=10^6, $Iter_{max}$=200 and Lim_{max}=100.

Firstly, the original outputs of the generators are calculated by minimizing the electricity purchase cost without constraints (9)-(11). Here, the output of the WFs and the loads are assumed to be independent and the correlation coefficients among load buses are r_L. Table 2 gives the details of the line congestion in condition of the original outputs with r_L=0, 0.2, 0.4, 0.5, 0.6, 0.8, 0.9, respectively. From Table 2, with r_L increased from 0 to 0.9, the standard deviation of the power flow through the congested line 6-8 grows from 3.7584MVA to 3.9340 MVA, which means a 4.67% increase, while the expected power flow has no significant increase. Also, if the confidence level of the chance constraints (9)-(10) is 0.95, branch 6-8 is the only congested line.

Fig. 3 illustrates the evolution of the congestion probability of branch 6-8 with r_L=0.5. As the line limit increase from 32MW to 40MW, the congestion probability decrease from 0.7662 to 0.0854. In order to obtain a wide range of feasible region for congestion management, the line limit of branch 6-8 is raised to 40MW. Table 4 gives the simulated results of the congestion management with r_L = 0.5 under different confidence levels. From the table, the cost of congestion management increases obviously with the confidence level raises, especially when $\alpha_i = \beta_i > 0.95$. What's more, when $\alpha_i = \beta_i = 0.97$, $Pen\_P > 0$ which means the line congestion can't be eliminate just by reschedule the generators. To avoid the violations without load shedding, the line connected with or near the WFs must be expanded.

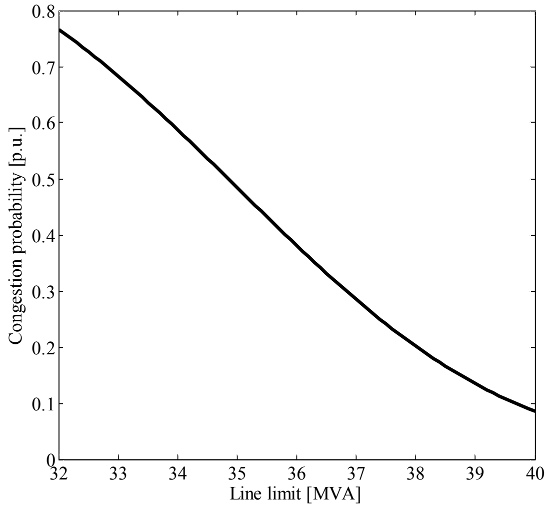

Fig. 3. Line limit (line 8-9) effect on the congestion probability

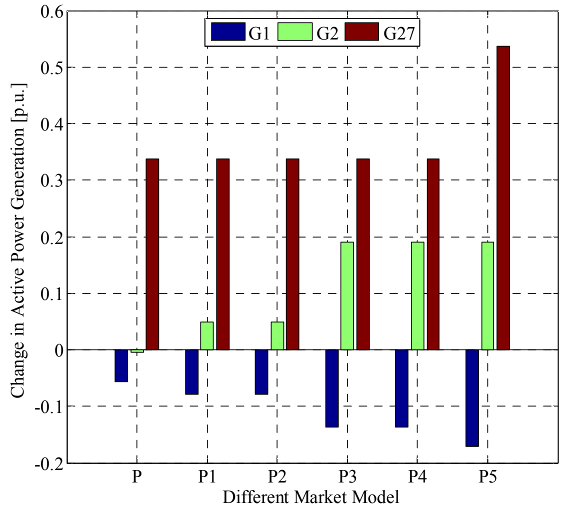

Fig. 4. Active power rescheduled of generators for modified 30-bus system

Table 4. Confidence level effect on results of congestion management (r_L=0.5)

$\alpha_i=\beta_i$	Probable congested line			Solution										
	Line	Congestion probability [p.u.]	Limit [MVA]	Expected flow [MVA]	Congestion probability [p.u.]	Outputs of generators [MW]						Congestion cost [$/h]	Pen_V	Pen_P
						G_1	G_2	G_{13}	G_{22}	G_{23}	G_{27}			
0.90	6-8	0.0854	40	34.7762	0.0854	99.72	26.02	12	15	10	11.80	0	0	0
0.93	6-8	0.0854	40	34.3999	0.0700	94.58	27.03	12	15	10	16.17	4.1960	0	0
0.94	6-8 6-28	0.0854 0	40 32	34.1156 10.2649	0.0600 0.0005	91.66	26.45	12	15	10	19.57	7.2926	0	0
0.95	6-8 6-28	0.0854 0	40 32	33.7879 11.1362	0.0500 0.0123	88.36	25.62	12	15	10	23.61	11.7253	0	0
0.96	6-8 6-28	0.0854 0	40 32	33.3951 13.3372	0.0400 0.0368	84.60	24.28	12	15	10	28.63	18.3981	0	0
0.97	6-8 6-28 25-27	0.0854 0 0	40 32 16	32.8969 16.8841 14.5302	0.0300 0.0930 0.0217	19.92	80	12	15	11.92	35	220	0	0.38

Table 5. Simulated cases for modified 30-bus system (total load 189.2MW)

Model	Probable congested line	Solution								
		Expected flow [MVA]	Congestion probability [p. u.]	Outputs of generators [MW]						Congestion cost [$/h]
				G_1	G_2	G_{13}	G_{22}	G_{23}	G_{27}	
P	6-8 6-28	33.7879 11.1362	0.0500 0.0123	88.36	25.62	12	15	10	23.61	11.7253
P1	6-8 6-28	33.7888 11.1319	0.0500 0.0122	83.88	30.00	12	15	10	23.60	12.5455
P2	6-8 6-28	33.7888 11.1319	0.0500 0.0122	83.88	30.00	12	15	10	23.60	12.5455
P3	6-8 6-28	33.7879 11.1335	0.0500 0.0122	72.48	41.20	12	15	10	23.62	22.2343
P4	6-8 6-28	33.7879 11.1335	0.0500 0.0122	72.48	41.20	12	15	10	23.62	22.2343
P5	6-8 6-28	33.2481 14.3340	0.0368 0.0500	65.41	41.20	12	15	10	30.58	65.0277

According to the previous study, the parameters of the system are set as follows: limit of line 6-8 is 40MW, r_L=0.5 and $\alpha_i=\beta_i$= 0.95. Different combinations of market structures comprising pool model and mix of pool plus direct electricity purchase contracts taken for study are:

P: pool model without direct electricity purchase contracts independent;

P1: pool model with one direct electricity purchase contract between buses 2–8;

P2: pool model with two direct electricity purchase contracts between buses 2–8 and 27–7;

P3: pool model with two direct electricity purchase contracts between buses 2–8, 12;

P4: pool model with three direct electricity purchase contracts between buses 2–8, 12 and 27-7;

P5: pool model with four direct electricity purchase contract between buses 2–8, 12 and buses 27–7, 24.

Here, we assume that each direct electricity purchase contract is the total active load consumption of the load bus, k=8 and w=10.

Table 3 gives the comparison results of the performance of ABC algorithm, EA [32] and PSO [32] for market structure P using the same population and iteration. From the table, the ABC algorithm has a better performance in the optimization results and can be used to solve the congestion problem properly.

The detailed simulated results and rescheduling of generators are present in Table 5 and Fig. 4. The table and the figure demonstrate that direct electricity purchase contracts decrease the feasible region of generation rescheduling. Comparing P1-P2 and P3-P4, the added contract between buses 27-7 have no effect on the existing contracts. However, some added contract may affect the rescheduling results significantly based on the comparison of P-P1, P1-P3 and P4-P5. Especially, in model P5, G_{27} needs to cut the contract by 0.92MW to make the system relieve the probable congestions. This can guide the generators to sign rational direct electricity purchase contracts.

5.2 Modified IEEE 57-bus case study

The modified IEEE 57-bus test system [31] consists of 7 generators, 80 branches and 42 load buses. WFs are located at bus 7 and 46 and each of them has 2 WFs with a correlation coefficient 0.9 and a power factor 0.9 lag. The two WF buses are correlated with a correlation coefficient 0.8 but they are both independent with other load buses. The characteristics of loads are set as the 30-bus system. Besides, we set the limit of branch 8-9 215MVA, r_L=0.5, α_i=β_i=0.95, w_V=109, w_P=109, $Iter_{max}$=200, Lim_{max}=100, k=8 and w=103. Table 6 gives the detailed data of generators for the modified 57-bus system.

Different combinations of market structures comprising pool model and mix of pool plus direct electricity purchase contracts are as follows:

C: pool model without any direct electricity purchase contracts.

C1: pool model with a direct electricity purchase contract between buses 6-8.

C2: pool model with two direct electricity purchase contracts between buses 6-8 and 8-12 (320MW).

C3: pool model with two direct electricity purchase contracts between buses 6-8, 13.

C4: pool model with three direct electricity purchase contracts between buses 6-8, 13 and 8-12 (320MW).

C5: pool model with three direct electricity purchase contracts between buses 6-8, 13 and 8-12 (350MW).

Table 6. Generator data for modified 57-bus system

Bus No.	P_{max} [MW]	P_{min} [MW]	Q_{max} [MW]	Q_{min} [MW]	Bidding coefficients	
					a	b
1	500	300	200	-140	0.0075	2.00
2	100	40	50	-30	0.0350	1.75
3	140	10	60	-10	0.1250	1.00
6	400	80	25	-40	0.01668	3.25
8	500	300	200	-140	0.0075	2.00
9	100	40	9	-10	0.0500	3.00
12	200	60	255	-150	0.0500	3.00

Bidding function: $f_B(P)$= a P + b \$/MWh

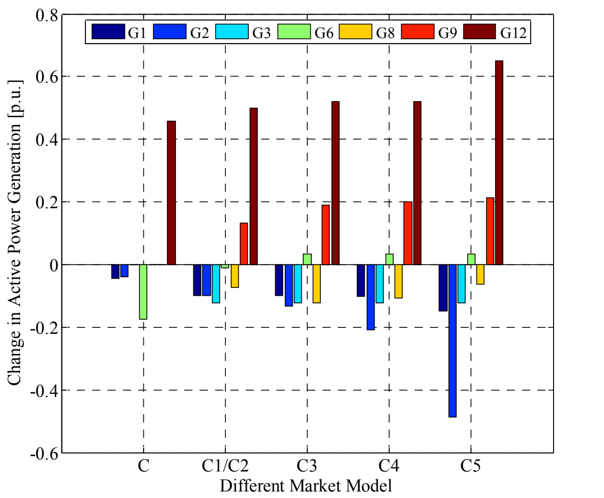

Fig. 5. Active power rescheduled of generators for modified 57-bus system

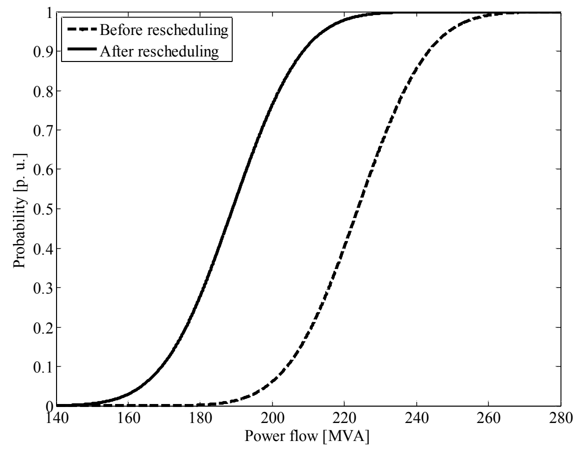

Fig. 6. CPD of power flow in line 8-9 (model C)

Here, all direct electricity purchase contracts are the total active load consumption of the lo ad bus except those with a brackets mark.

Table 7 and Fig. 5 depict the simulated results for modified IEEE 57-bus system in different market structures. Original outputs of generators are optimization results aiming to minimize the electricity purchase cost without constraints. From Table 7, congestion cost increases as the

Table 7. Simulated cases for congested line 8-9 in modified 57-bus system (total load 1250.8MW)

Model	Solution									
	Expected flow [MVA]	Congestion probability [p. u.]	Outputs of generators [MW]							Congestion cost [$/h]
			G_1	G_2	G_3	G_6	G_8	G_9	G_{12}	
Original	223.7648	0.6121	409.19	88.79	27.09	154.75	373.24	63.43	66.92	0
C	188.9704	0.0408	386.77	84.94	27.15	85.41	373.55	63.50	158.70	1107.8421
C1	185.4570	0.0078	359.97	78.82	10	150.01	336.50	76.68	166.77	1311.3427
C2	185.4570	0.0078	359.97	78.82	10	150.01	336.50	76.68	166.77	1311.3427
C3	175.2216	0	359.83	75.50	10	168.06	311.83	82.34	170.76	1486.2954
C4	180.0232	0	357.96	67.89	10	168	320	83.56	170.76	1495.0329
C5	189.8497	0.0500	334.33	40	10	167.93	341.65	84.76	196.91	2759.9625

Table 8. Simulated cases in nodal pricing for modified IEEE 30-bus system (total load 189.2MW)

Model	Probable congested line	Solution								
		Expected flow [MVA]	Congestion probability [p. u.]	Outputs of generators [MW]						Congestion cost [$/h]
				G_1	G_2	G_{13}	G_{22}	G_{23}	G_{27}	
N	6-8 6-28	33.7876 11.2037	0.0500 0.0137	53.45	52.68	12.00	20.87	12.38	22.40	67.1183
N1	6-8 6-28	33.7882 11.1835	0.0500 0.0133	56.01	51.21	12.00	20.34	11.48	22.80	73.3141
N2	6-8 6-28	33.7878 11.2841	0.0500 0.0147	56.01	51.21	12.00	20.34	11.48	22.80	73.3141
N3	6-8 6-28	33.7879 11.1806	0.0500 0.0133	56.01	51.21	12.00	20.34	11.48	22.80	73.3141
N4	6-8 6-28	33.7878 11.2443	0.0500 0.0141	56.01	51.21	12.00	20.34	11.48	22.80	73.3141
N5	6-8 6-28	33.2585 14.3340	0.0370 0.0500	50.34	54.88	12.00	16.48	10.00	30.25	112.0610

number of direct electricity purchase contracts grows overall. Some direct electricity purchase contracts added to the system have no effects on the original system (comparing C1-C2) but some may have (comparing C3-C4). In C5, in order to remove the congestion the contract between buses 8-12 is decreased by 8.35MW. As a result, signing direct electricity purchase contracts rationally can help relief congestion somehow. Cumulative probability distribution (CPD) of branch 8-9 before and after rescheduling for market structure C is presented in Fig. 6. The value of the power flow range decrease obviously through the rescheduling.

5.3 Nodal pricing model case study of IEEE 30-bus

All the relative parameters in this part are set as the same as those in 5.1. Similar to the previous case studies, different combinations of market structures comprising nodal pricing model and mix of nodal pricing plus direct electricity purchase contracts are assumed, namely N, N1, N2, N3, N4, N5, respectively.

Table 8 shows the simulated optimization results for modified IEEE 30-bus system in nodal pricing model under different direct electricity purchase contracts. Based on the table, similar concolusions as those in 5.1 can be obtained. However, as the settlement of congestion cost in the nodal pricing model is quite different from that in the pool model, the results in Table 8 are quite different from those in Table 5. This indicates that suitable scheduling approaches should be adopted in different market modes. Also, Table 8 demonstrates that the proposed congestion management model capable of processing uncertainties and correlations can be adoptd in the nodal pricing model.

6. Conclusion

In this paper, a new congestion management approach based on probabilistic power flow has been presented to process uncertainties and correlations in congestion problem. The probabilistic power flow model has been formed based on the combined method of 2m+1 PEM and Cholesky decomposition. An optimal probabilistic power flow model minimizing the congestion cost considering market structures with pool, nodal pricing and direct electricity purchase contracts has been studied. The simulated results on the modified IEEE 30-bus system and IEEE 57-bus system reveal the following conclusions.

1) The correlations between buses with WFs or loads have significant effect on the congestion probability but little effect on the expected power flow.
2) Higher confidence level leads to more congestion cost. Dispatchers can select appropriate confidence level according to the demand of system operation.
3) The congestion management approach based on probabilistic power flow provides a way to balance both congestion cost and congestion probability.

4) Signing direct electricity purchase contracts rationally can help relief the congestion without burdening generation rescheduling.
5) The proposed congestion management model can be used in both pool and nodal pricing model.

Acknowledgements

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Xu Wang He received the B.S. degree in electrical engineering from Southeast University, Nanjing, China, in 2010. Currently, he is pursuing the Ph.D. degree in the School of Electronic Information and Electrical Engineering, Shanghai Jiao Tong University, Shanghai, China.

Chuan-Wen Jiang He received the M.S. and Ph.D. degrees from Huazhong University of Science and Technology, Wuhan, China, in 1996 and 2000, respectively, and completed his post-doctoral research in the School of Electronic Information and Electrical Engineering, Shanghai Jiao Tong University, Shanghai, China, in 2002. He is a Professor with the School of Electronic Information and Electrical Engineering, Shanghai Jiao Tong University. He is currently researching reservoir dispatch, load forecast in power systems, and the electrical power market.