Non-dominated Sorting Differential Evolution Algorithm for Multi-objective Optimal Integrated Generation Bidding and Scheduling

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***Abstract*—According to the relationship of coordinated interaction between unit output and electricity price, an economic/risk/environmental generation optimal model for maximizing total profits in the dealing day and minimizing both risk and emissions was formulated in this paper. A new multi-objective differential evolution optimization algorithm, which integrated Pareto non-dominant sorting and differential evolution algorithm and improved individual crowding distance mechanism and mutation strategy to avoid premature and unevenly search, was designed to achieve Pareto optimal set of this model. Moreover, fuzzy set theory was employed to extract the best compromise non-dominated solution. The simulation analysis of an example demonstrated the superiority of the proposed algorithm such as integrality of Pareto front, well-distributed Pareto-optimal solutions, high search speed and so on. The proposed approach can effectively solve the multi-objective decision-making optimization problem of generation bidding.**

Keywords—non-dominant sorting; differential evolution; electricity market; generation

I. INTRODUCTION

Nowadays, generation bidding has been a general trend. Meanwhile, as a main air pollution source, it is an inevitable problem for thermal power plants to control and govern emissions. However, there are still few studies on output optimization by time-interval and generation bidding on generating side to realize energy conservation and environmental protection, low bidding risk and high profits. An economic/risk/environmental generation optimization model based on market price prediction curve in the dealing day for maximizing profits and minimizing both risk and emissions, which considering atmospheric emission and bidding risk coefficient, is established. The multi-objective optimal unit operation schemes can be achieved from the model and thus to form the optimal generation bidding plan of generation side. Since the economic/risk/environmental generation optimization model has characteristics of unsmooth, non-convex and objectives coupling, and the scales of each objective are different, there is always no such absolute optimal solution to optimize all objectives. Only trade-off solutions would be made to optimize each objective as much as possible through coordination and compromise. It is difficult to solve such multi-objective problems by conventional methods. Followed by the development of multi-objective evolution algorithm, a series of multi-objective optimization algorithm, such as genetic algorithm, particle swarm optimization, ant colony optimization etc, came out and have been made considerable progress [1]-[3]. However, the drawbacks such as unstable convergence, unevenly distribution of non-dominated solutions and low speed hindered the application of those algorithms. So, a more effective and simpler algorithm, the new multi-objective differential evolution algorithm, is proposed in this paper. The validity is verified by example.

II. MULTI-OBJECTIVE PROBLEM OF GENERATION BIDDING

A. Objective Functions

1) Objective Function of Bidding Risk

Market electricity price is the core of electricity exchange in market environment. The bidding reference base can be determined by short-term prediction of market electricity price. The characteristic of generation bidding leads to the contradiction between high quotation with high risk and low quotation with low profit. Here, as a dispatch period, one dealing day is divided into 24 time-intervals. The maximal absolute error of price prediction W_n in time-interval n can be determined by statistics and analysis of historical prediction data. Suppose p_n' is market prediction price in time-interval n, and the actual bid price is p_n, then the objective function of minimal bidding risk in time-interval n can be defined as:

$$\min.\ v_n = 10 - \frac{10(p_n' - p_n)}{W_n} \tag{1}$$

where v_n is defined as bidding risk coefficient of time-interval n. it should be less than 10. Otherwise the failure probability would be greater. Moreover, the risk coefficient v should be the same every time-interval in one dealing day.

2) Objective Function of Generation Profit

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Comprehensively considering generation fuel cost, unit start-up/shut-down cost, fixed cost analysis and bidding risk analysis, the objective function of maximizing generation profit in one dealing day is:

$$\min.\ -G(u,q) = -\sum_{n=1}^{24}\{\text{xor}(q_n,0)[q_n p_n + (q_{\max} - q_n) r_n - C_n] - C_{\text{fa}} - u_{n-1}(1-u_n)D - u_n(1-u_{n-1})S\} \quad (2)$$

where G is generation profit of one unit in one deal day; *xor()* is exclusive-or operation; q_n is actual unit output power in time-interval n; q_{max} is maximum output power of the unit; r_n is spinning reserve capacity price; u_n is 0/1 variable which represents the operation status of the unit where 0 means shut-down and 1 start-up. If u_{n-1} is 1 while u_n 0 then there will be shutdown cost. Otherwise if u_{n-1} is 0 while u_n 1 then there will be start-up cost. C_{fa} is average fixed cost and can be achieved by divided the total fixed cost into each time-interval; D as the shut-down cost can be regarded as a constant; Fuel cost C_n and Unit start-up cost S can be calculated by (3) and (4), respectively.

$$C_n = a q_n^{\,2} + b q_n + c + \left| g \sin(h(q_n - q_{\min})) \right| \quad (3)$$

$$S = K_0 + K_1(1 - e^{-T/\tau}) \quad (4)$$

where a, b, c represent characteristics parameters of fuel cost curve; q_{min} is minimum output of the unit; g and h are valve point effect parameters; K_0 is the turbine start-up cost and K_1 is the start-up cost while the boiler has been fully cooled; T is shut-down duration and τ is boiler cooling time constant.

3) Objective Function of Atmospheric Pollutants

The atmospheric pollutants caused by power plant mainly include CO_2, SO_2, NO_x, and so on. The relationship between each atmospheric pollutant and generation can be modeled separately. Here, the paper adopts the atmospheric pollutants comprehensive emission model[3]. The objective function of atmospheric pollutants is:

$$\min.\ E = \sum_{n=1}^{24}\left\{10^{-2}(\alpha q_n^{\,2} + \beta q_n + \gamma) + \xi \exp(\lambda q_n)\right\} \quad (5)$$

where α_i、β、γ、ξ and λ are coefficients of emission characteristics of the ith generator and can be achieved by applying least squares on monitoring data of unit emission.

B. Constraints

1) Generation Capacity Constraint:

$$q_{\min} \le q \le q_{\max} \quad (6)$$

where q_{min} and q_{max} are the lower and upper real power output limits, respectively.

2) Constraints of Unit Least Continuous Operating Time and Least shut down time:

$$\begin{cases} [T_{n-1}^{\mathrm{U}} - T_{\min}^{\mathrm{U}}][u_{n-1} - u_n] \ge 0 \\ [T_{n-1}^{\mathrm{D}} - T_{\min}^{\mathrm{D}}][u_n - u_{n-1}] \ge 0 \end{cases}, \ (n=1,2,\ldots,24) \quad (7)$$

where T_{n-1}^{U} and T_{n-1}^{D} are continuous operating time and shut down time in time-interval *n-1*, respectively; $T_{\min}^{\mathrm{U}}$ and $T_{\min}^{\mathrm{D}}$ are unit least operation time and least down time, respectively, normally on an hourly basis.

3) Constraints of Unit Output Variation Rate while operating:

$$-R_{\mathrm{d}}\Delta t \le \Delta q_n \le R_{\mathrm{u}}\Delta t \ \ (n=1,2,\ldots,24) \quad (8)$$

4) Constraints of Unit Output Variation Rate While Startup or Shutdown:

$$-K_{\mathrm{d}}\Delta t \le \Delta q_n \le K_{\mathrm{u}}\Delta t \ \ (n=1,2,\ldots,24) \quad (9)$$

where Δq_n is variation quantity of output in time-interval n; R_d and K_d are permissible descending velocity while operating and shutdown, respectively; R_u and K_u are permissible rising velocity while operating and startup, respectively.

The multi-objective optimization model of economic/risk/environmental generation bidding in one dealing day is formed by synthesizing all objective functions and constraints mentioned above.

III. DESIGN OF MULTI-OBJECTIVE DIFFERENTIAL EVOLUTION ALGORITHM

A. Description of Multi-objective Optimization Problem

Taking a multi-objective minimization problem with a set of constraints as an example, the mathematical description of MOP can be described as:

$$\min . f_i(X),\ i = 1,2,\ldots,N_{obj}$$
$$s.t. \begin{cases} X = (x_1, x_2, \cdots, x_d) \in R^d \\ g_j(X) \le 0, j = 1,2,\ldots,J \\ h_k(X) = 0, k = 1,2,\ldots,K \end{cases} \quad (10)$$

where $f_i(X)$ is objective functions; X is d-dimension decision-making vector; N_{obj} is the number of objective functions; $g_j(X)$ is inequality constraint function and $h_k(X)$ is equality constraint function.

To evaluate the superiority-inferiority of solutions of MOP, the following definitions are frequently used.

For decision-making vector A and B,

1) Pareto Dominance: $A \prec B$ if and only if

$$\begin{cases} f_i(A) \le f_i(B), \forall i \in \{1,2,\ldots,N_{obj}\} \\ f_j(A) < f_j(B), \exists j \in \{1,2,\ldots,N_{obj}\} \end{cases} \quad (11)$$

2) Pareto Optimal or Pareto Non-dominated: Solution A is Pareto optimal (Pareto non-dominated) Solution if and only if

$$\neg \exists X \in R^d : X \prec A \quad (12)$$

Equation (11) and (12) should meet the constraints given in (10).

The set of all Pareto optimal is called Pareto optimal set. The values of objective functions corresponding to the Pareto optimal are called non-dominated objective vector. The area formed by all non-dominated objective vectors is called Pareto front. To solve MOP actually is to find Pareto optimal as much as possible and distribute their corresponding objective vectors evenly on Pareto front.

B. Pareto Non-dominant Sorting and Selection

In recent years, multi-objective evolutionary algorithms (MOEAs) have become a research focus because they need not measure the weighting relationship between each objective accurately but find optimal solution set by its great global search ability. One of the most effective and commonly used MOEAs is NSGA-II. It improves conventional non-dominated sorting genetic algorithm (NSGA) [4] by adopting fast sorting of Pareto non-dominated solutions, elitism preservation and selection operator based on sorting grade of solution and crowding distance. And its performance has been improved greatly. More details about NSGA-II procedure are in [1].

At the same Pareto non-dominated sorting grade, the greater the crowding distance value of individual is, the sparser the area where it situated is, and that means that the more valuable the individual in the area is and the more it should be kept in evolution process. The selection operation in NSGA-II works according to this principle. Suppose individual A and C are individuals before and after individual B, respectively, then the crowding distance $D_c(B)$ of individual B (sparseness) in NSGA-II can be calculated by the formula below.

$$D_c(B) = \sum_{i=1}^{N_{obj}} \left| f_i(A) - f_i(C) \right| \tag{13}$$

where $f_i(A)$ and $f_i(C)$ are the ith objective function values of individual A and C, respectively. The crowding distance of the individuals on border are defined as infinite to assure them to be selected into next generation unconditionally.

However, the sparseness of individual B is related not only to the size of neighborhood but also to its distribution in neighborhood. So applying (13) to evaluate the distance crowding may result in elimination of some well distributed individuals and retention of some badly distributed ones. The diversity of solutions would decrease and their distribution would be unevenly followed by the progress of evolution. Then the solutions cannot converge to Pareto front evenly and accurately. So in this paper, the crowding distance is calculated as follows (O is the center point between A and C):

$$\begin{aligned} D_c(B) &= \sum_{i=1}^{N_{obj}} (\left| f_i(A) - f_i(C) \right| - \left| f_i(B) - f_i(O) \right|) \\ &= \sum_{i=1}^{N_{obj}} (\left| f_i(A) - f_i(C) \right| \times 0.5 + \\ &\qquad \min[\left| f_i(A) - f_i(B) \right|, \left| f_i(B) - f_i(C) \right|]) \end{aligned} \tag{14}$$

where $f_i(B)$ and $f_i(O)$ are values of individual B and the center point O of the ith objective function, respectively.

Equation (14) can comprehensively reflect that the crowding distance of individual B is related not only with neighborhood size of the objective function (represented by $\left| f_i(A) - f_i(C) \right|$) but also with distribution evenness (represented by $\left| f_i(B) - f_i(O) \right|$, the distance between the individual and the center of neighborhood). That is, $\left| f_i(A) - f_i(C) \right| \uparrow$ or $\left| f_i(B) - f_i(O) \right| \downarrow$, $D_c(B) \uparrow$.

Since NSGA-II adopted the crossover and mutation mechanism of genetic algorithm, the disadvantages of genetic algorithm such as instable convergence, slow speed and easy to premature exist in NGSA-II as well. Therefore, the paper proposes the non-sorting differential algorithm by substituting genetic operation in NSGA-II algorithm with differential evolution operation.

C. Differential Evolution Algorithm

Differential evolution algorithm (DEA) is a simple but effective intelligent optimization algorithm presented firstly by Rainer Storn and Kenneth Price in 1995. It needs no encoding and decoding. And with its fast convergence, good stability and strong adaptability to all kinds of non-linear functions, it is proved to be better than those algorithms such as genetic algorithm, particle swarm optimization algorithm, evolution strategy, adaptive simulated annealing and so on. The description of DEA procedure can be found in [5]. In differential evolution, suppose the population size is N_p, then each individual vector of the Gth generation can produce middle individual $Y_{i,G+1}$ by mutation through (15), (16) or (17) according to practical effect.

$$Y_{i,G+1} = X_{r_3,G} + F \cdot (X_{r_1,G} - X_{r_2,G}) \tag{15}$$

$$Y_{i,G+1} = X_{best,G} + F \cdot (X_{r_1,G} - X_{r_2,G}) \tag{16}$$

$$Y_{i,G+1} = X_{i,G} + F \cdot (X_{best,G} - X_{i,G}) + F \cdot (X_{r_1,G} - X_{r_2,G}) \tag{17}$$

where $i, r_1, r_2, r_3 \in \{1, 2, \ldots, N_p\}$; r_1, r_2 and r_3 are randomly chosen and $r_1 \neq r_2 \neq r_3$; $X_{best,G}$ is the best individual vector of the Gth generation; mutation scaling factor F is a real constant from the interval [0,2].

According to the structure principle of each formula, (15), (16) and (17) can be named as DE/rand/1, DE/best/1 and DE/local-to-best/1, respectively, to distinguish different mutation strategies from each other in differential evolution progress. After comparison, the paper adopted the mutation strategy as shown in (18) which is achieved by (16) after the introduction of jitter variation.

$$Y_{i,G+1} = X_{best,G} + [F + (1-F) \cdot rand](X_{r_1,G} - X_{r_2,G}) \tag{18}$$

where *rand* is a random real number from the interval [0,1].

Then, through crossover between objective individual vector $X_{i,G}$ and middle individual vector $Z_{i,G+1}$ by (19), a candidate individual of next generation $Z_{i,G+1}$ is produced to maintain the diversity of population.

$$\begin{aligned} &X_{i,G} = (x_{i,1}, x_{i,2}, \cdots, x_{i,d}),\ Y_{i,G+1} = (y_{i,1}, y_{i,2}, \cdots, y_{i,d}) \\ &Z_{i,G+1} = (z_{i,1}, z_{i,2}, \cdots, z_{i,d}),\ z_{i,j} = \begin{cases} x_{i,j}, & R_j > C_R \\ y_{i,j}, & \text{Others} \end{cases} \end{aligned} \tag{19}$$

where $j \in \{1,2,\ldots,d\}$; R_j is a random real number from the interval [0,1]; crossover probability factor C_R is a random real number from the interval [0,1].

D. NSDEA Procedure

Based on the improved Pareto non-dominated sorting and differential evolution algorithm, the procedure of non-dominated sorting differential evolution algorithm (NSDEA) for solving multi-objective optimization problem of generation bidding is shown as follows.

According to the initial unit status of the first time-interval and all constraints, randomly produce 24 output values at the end of each time-interval as the individual codes in turn. Then randomly produce the bidding risk coefficient from the interval [0, 10] as the 25^{th} code. The initial parent population U_0 is formed by m real-coded individuals with the length of 25. The initial child population S_0 is empty. Calculate values of each objective function in U_0, and then enter the following cyclic iterative progress.

While g$\leqslant$ G_{max} {

Step 1 (population mixture): combine child population S_g and parent population P_g into a temporary population M_g. All repeated individuals are forced to be locally mutated to assure all the individuals in the population are different from each other. And then calculate values of each objective function of all new-born individuals with (6).

Step 2 (Pareto non-dominated sorting): according to Pareto non-dominated sorting strategy, compare objective function values of each individual to find Pareto non-dominated individual set in current population to compose *Ps(1)*. Remove all the individuals in *Ps(1)* from the current population. And then find new Pareto non-dominated individual set to compose *Ps(2)*. Repeatedly to do so until all individuals are finished sorting. Then calculate crowding distances of each individual in each grade by (11).

Step 3 (parent population update): fill *Ps(1)*, *Ps(2)*... into an empty population in turn until the population scale would exceed m if further filling. And then fill individuals into *Ps(i)* according to crowding distance from big to small till the population scale is m. Thus form new parent population $P_{g+1.}$

Step 4 (child population update):

a. (championship selection): applying random championship to generate optimal population from P_{g+1} according to the principle of the smaller of the sorting grade the prior and the greater of crowding distance the prior at the same grade. The size of optimal population is generally half of the size of parent population.

b. (differential evolution): applying mechanism of mutation and crossover of DE analyzed above to produce new child population $S_{g+1.}$

Step 5: g=g+1 and enter the next cycle.}

The final parent population is the Pareto optimal set of the multi-objective optimal problem.

E. Best Compromise Solution

In practical operation, there is usually only one of the schemes to be put into practice. The decision-maker has to select one optimal compromise solution from the Pareto optimal set. Here, the best compromised solution can be determined by fuzzy set theory [6]. The corresponding satisfaction degree of each objective function of each Pareto optimal can be represented by fuzzy membership function. The definition is:

$$h_i = \begin{cases} 1, & f_i \le f_i^{\min} \\ \dfrac{f_i^{\max} - f_i}{f_i^{\max} - f_i^{\min}}, & f_i^{\max} > f_i > f_i^{\min} \\ 0, & f_i \ge f_i^{\max} \end{cases} \tag{20}$$

where $i \in \{1,2,\ldots,N_{obj}\}$; f_i is objective function; N_{obj} is the number of objective function; f_i^{max} and f_i^{min} represent maximum and minimum value of the ith objective function, respectively; h_i is either 0 or 1 where 0 represent full dissatisfaction and 1 satisfaction to the ith objective function value.

Then, apply (21) to achieve standard satisfaction degree of each solution in Pareto optimal set:

$$h = \frac{1}{N_{obj}} \sum_{i=1}^{N_{obj}} h_i \tag{21}$$

After comparison, the Pareto optimal with the greatest value of h is determined to be the best compromise solution.

IV. EXAMPLE AND ANALYSIS

The unit parameters of one generation plant are shown in table I. The initial unit status is: having been operating for 3 hours; the output is 200MW. The prediction value of market clearing price and spinning reserve price are as in [7].

TABLE I. UNIT PARAMETERS

a/(Yuan/MW^2.h)	b/(Yuan/MW.h)	c/(Yuan/h)	g/(Yuan/h)	h/(rad/MW)
0.102	87.38	6120.63	450	0.082
K_0/Yuan	K_1/Yuan	τ/h	C_{fa}/(Yuan/h)	D/Yuan
0	23280	4	10385	980
α/(t/MW^2.h)	β/(t/MW.h)	γ/(t/h)	ξ/(t/h)	λ/MW.h
6.213e-4	-5.849e-2	8.510	5e-4	0.019
q_{min}/MW	q_{max}/MW	T_{min}^{D} / h	T_{min}^{U} / h	
160	350	3	4	
R_d/(MW/h)	R_u/(MW/h)	K_d/(MW/h)	K_u/(MW/h)	
120	70	200	150	

Fig. 1 is the Pareto front with profit and emission as its objective while bidding risk is 8 by NSDEA (G_{max} is 300, m is 120, F is 0.3 and C_R is 0.5). For comparison, Fig. 2 shows the result achieved by NSGA-II to the same problem (G_{max} is 500, m is 120, crossover probability is 0.95 and mutation probability is 0.05). It is apparently that NSDEA is superiority in optimization speed, integrality of Pareto front and distribution of non-dominant solution comparing with conventional NSGA-II.

After considering profit of dealing day, bidding risk and emissions, the Pareto fronts are shown in Fig. 3 (by NSDEA) and Fig. 4 (by NSGA-II), respectively. It can be seen that the Pareto front achieved by NSDEA is more complete and smooth than by NSGA-II. Moreover, the non-dominated solutions distributes more evenly as well.

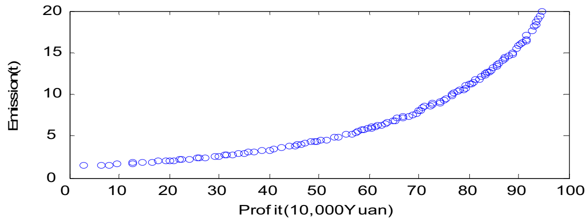

Figure 1. The Pareto front of NSDEA(two objectives)

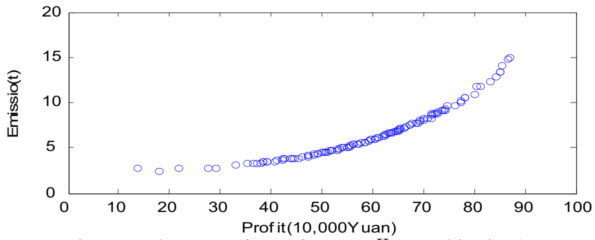

Figure 2. The Pareto front of NSGA- II (two objectives)

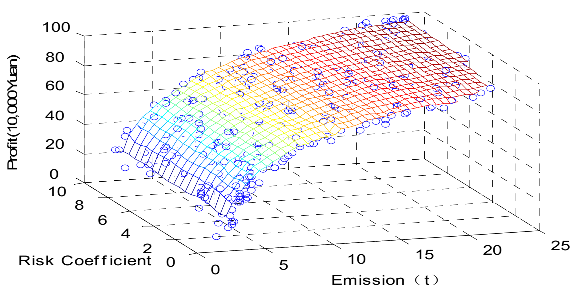

Figure 3. The Pareto front of NSDEA(three objectives)

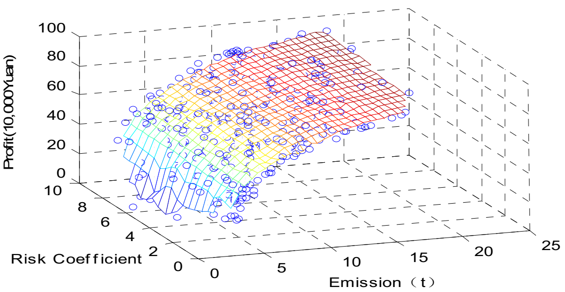

Figure 4. The Pareto front of NSGA- II (three objectives)

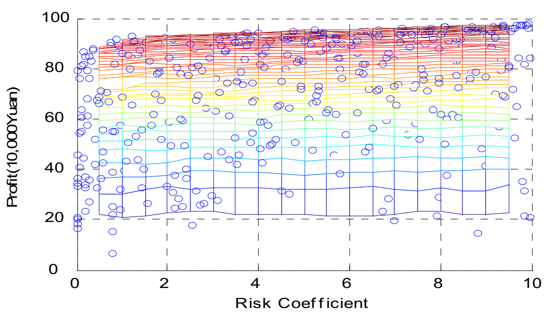

Figure 5. The equatorial projection of profit-risk

The two-dimension plane projection considering bidding risk and profit achieved from Fig. 3 is shown in Fig. 5. It is clear that high profit can be achieved with low bidding risk. From the up front of the projection, it shows that the probable maximum profit rises after the rising of bidding risk without considering emissions.

The optimal compromise solution of unit output plan in one dealing day is shown in Fig. 6. In this plan, the bidding

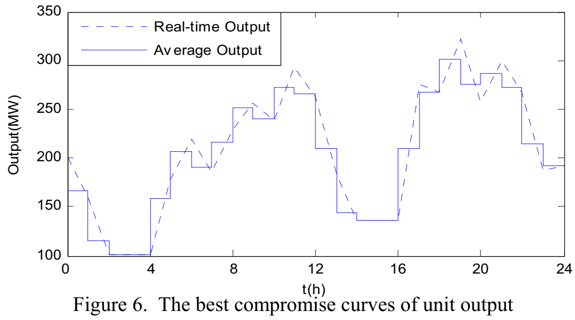

Figure 6. The best compromise curves of unit output

risk coefficient is 0.102, the profit is 634128.26 yuan, and total emission is 7.029 ton. It is clear that high profit can be achieved with low bidding risk and emissions.

V. CONCLUSIONS

NSDEA proposed in this paper is an organic integration of Pareto non-dominated sorting and differential evolution algorithm. It improves individual crowding mechanism and mutation strategy effectively. Its performance is superiority for solving multi-objective optimal problem of generation bidding for maximizing profits and minimizing both risk and emissions. It can realize global multi-objective optimization easily and quickly, achieve accurate and complete Pareto front and get the best compromise solution automatically. It can provide effective instruction for power provider to make scientific and reasonable bidding schemes for power market by the economic/risk/environmental generation optimization method.

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