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A New Green Revenue Management Model for Wind Power

Qian Zhang

Abstract—**Wind energy is no doubt the most competitive low carbon energy. Many traditional power plants have also set up wind parks. Due to the randomness of the wind power output, power plant faces the problem of how to make a dispatch plan for its power generation units when the load demands is confirmed from the electric power market in advance. This paper presents a green revenue management model for power plants with wind parks under an uncertain power out put condition. Generation cost, spinning reserve cost and external cost (emission) are all taken into account. The model has a stochastic programming formulation designed to capture the randomness of wind power output. A novel approach of robust optimization and ant colony algorithm are applied to solve the problem on a scenario-basis. Decision-makers' risk aversion is considered in the objective function. Mean absolute value is used to measure risk of deviation of revenue from its expected value. As the external cost of carbon emission and the randomness of the wind power output are considered in the model, the result presents a robust dispatch plan for the power plant, which can achieve good benefit.**

Index Terms—**green revenue management; colony algorithm; power plant; wind power.**

I. Introduction

A revenue management system involves application of information systems and pricing strategies to allocate the right capacity to the right customer at the right price at the right time. Wind energy is no doubt the most competitive low carbon energy [1, 2]. this paper presents a revenue management model for power plants with wind parks. Generation cost of the traditional thermal unit, its spinning reserve, its external cost (emissions) and wind power cost are taken into account. Under the restriction of power demand and unit operations requirements, running condition and output of each unit are confirmed for a certain period of time. As the external cost of carbon emission and the randomness of the wind power output are considered in the model, the result presents a robust dispatch plan for the power plant, which can achieve good benefit for the generator and the environment.

As a complex engineering problem, the green revenue problem is a multi-variable, multi-constrained, discrete non-linear optimization process[3]. There are some algorithms for this problem, such as the priority list method [4], dynamic programming [5], Lagrangian relaxation [6, 7], genetic algorithm [8, 9], the direct search method [10], particle swarm method [11-13] and simulated annealing method [14] and so on. In this paper, the Ant colony algorithm is adopted.

II. The Green Revenue Model for Power Plants with Wind Parks

The development of wind power depends on supportive policies from the government as its cost is high. It is almost impossible for wind power to win the market in terms of cost if there are no government price subsidies. Also, external cost of CO2 emission by thermal units should be introduced. This is a price leverage to increase the competitiveness of wind power.

In the traditional system, the aim of unit dispatch is to achieve optimal economic operations and, therefore, the objective function is the lowest power generation cost. With the development of Chinese power industry reformation, power plants have to compete with each other for grid tenders. The cost of each power plant has become a business secret. Plants establish their market strategies on the basis of revenues. It is reasonable to set up a green revenue management model to make generation plans on the basis of demand forecasting

A. The revenue of wind power output

As a clean energy, wind power is encouraged and supported by the government through methods such as priority dispatch, full acquisition and so on. Priority dispatch means power generated by the wind park will be purchased by the grid without considering the cost. The revenue model of the wind park is as shown in the following equation where wind power price includes price subsidies from the government.

The wind park revenue model is as follows:

$$R_W = \sum_{t=1}^{T}\sum_{j=1}^{M}\left[P_{Wj}^t \cdot Q_{Wj}^t - C_{Wj}^t \cdot Q_{Wj}^t\right] \qquad (4)$$

T: total dispatching period
t: dispatching period no.
M: number of wind park units
j: wind park unit no.
$P_{wj}{}^t$: power price of unit j in t period.
$Q_{wj}{}^t$: power number of units j in t period.
$C_{wj}{}^t$: generation cost per unit j in t period.

B. The green revenue model of power plants including Wind Park

Considering all the above stated conditions, the green revenue model of the power plant including a wind park is as follows:

$$R=\sum_{t=1}^{T}\sum_{i=1}^{N}\begin{bmatrix}P_i^t\cdot Q_i^t-C_i^t\cdot Q_i^t-S_i^t\left(1-U_i^{t-1}\right)\\ -k_{ri}\cdot r_{upi}^t-K_{co2i}P_{co2}p_i^t\end{bmatrix}$$
$$+\sum_{t=1}^{T}\sum_{j=1}^{M}\left[P_{Wj}^t\cdot Q_{Wj}^t-C_{Wj}^t\cdot Q_{Wj}^t\right] \quad (5)$$

III. STOCHASTIC FORMULATION AND ROBUST OPTIMIZATION SOLUTION SCHEME

Due to the intermittent and non-controllable characteristics of wind speed, the output and the start and stop conditions of Wind Park are stochastic. While it is not possible to remove the uncertainty fully, the best way to make decisions under an uncertain environment is to accept uncertainty first, and then understand uncertainty and incorporate it into the planning decision model. Stochastic programming tools are based on this idea. Robust optimization is one of the proactive approaches used to solve stochastic problems which represent integration of goal programming and scenario-based description of unknown data. We define the following measurements of robustness:

Definition 3.1 (Solution robustness): An optimal solution is solution robust with respect to optimality if it remains " close" to the optimal for any scenario $s\in\Omega$.

Definition 3.2 (Model robustness): An optimal solution is model robust with respect to feasibility if it remains "almost " feasible for any scenario $s\in\Omega$.

Since the decision-maker usually faces different scenarios because of demand uncertainty, we assume that the decision-maker has a set of scenarios $s\in\Omega=\{1,\ 2,\ \cdots,\ S\}$ associated with unknown parameters. For each scenario, the corresponding probability is p_s, such that $p_s\geq 0$ and $\sum_{s=1}^{S}p_s=1$.

The philosophy of robust optimization is built on the trade-off between solution robustness and model robustness. A stochastic programming model is obtained, and an absolute deviation is used in this model to measure the risk of falling revenues.

Denote this formulation as:

$$\text{Max}\ \sum_{s=1}^{s}p_sR^s-\theta\sum_{s=1}^{s}p_s\left|R^s-\sum_{s=1}^{s}p_sR^s\right|$$
$$-\sum_{s=1}^{s}p_s\sum_{i=1}^{T}w_t\left|\sum_{i=1}^{N}p_i^t\cdot U_i^t+\sum_{j=1}^{M}p_{wj}^{St}-D^t\right| \quad (7)$$

where θ and w_t are non-negative weighting factors. Together, these two terms can be viewed as a measure of the trade-off solution's robustness.

The first term in the objective function is the expected revenue of the power plant, and the second term is the mean absolute deviation of revenue. Parameter θ can be regarded as a risk-aversion factor (risk trade-off factor) for the decision-maker. The different values of risk factors represent the different risk aversions of decision-makers. In the following section, we show that the expected revenue decreases with increase in the risk-aversion factor.

The absolute deviation in the third term is a model robustness measure and parameters w_t are penalty factors for constraint violations. In this paper, the actual power generated by the thermal power unit and the wind power unit should as same as that of the power load the power plant won from the power market. Otherwise there will be the loss for the generator. In power load peak period, this condition will be more restrict as the cost will be more to adjust the working condition of all the units. The decision-maker may adjust thermal power supply durations by changing the corresponding weighting w_t , by using the mean absolute values as penalties; the model can generate solutions which are robust in all scenarios.

IV. THE IMPROVED ANT COLONY ALGORITHM

Ant colony algorithm is a random heuristic optimization algorithm based on groups [15, 16]. Its basic idea is that ants always search for the shortest path between food sources and the nest: the ants release some material called pheromones along the way when they are searching and tend to follow the path with pheromones of high concentrations. This group behavior ultimately results in the shortest path between food sources and the nest.

To implement the above idea, the "artificial ants" concept was introduced in algorithms which select the path according to probability p, while path probability p is a function of traces of pheromone. This algorithm is able to find a new path for each iteration as it releases a certain amount of pheromones, whose value has a function related with the size and optimization results.

Although individual ants in the group select their paths randomly, the positive feedback and local search are achieved by mutual information collaboration. By searching neighborhood new paths, the global search is realized.

Ant k changes its direction during the process of searching, that is to say, it selects the node leading to a new path. This decision process depends on values of pheromone on available paths. The state transition probability of ant K in city I of selecting J, is defined as follows:

$$p_{ij}^k(t)=\begin{cases}\dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}}{\sum\limits_{s\in allowed}\left[\tau_{is}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}},\ j\in allowed_k\\ 0\end{cases} \quad (8)$$

Where $\eta_{ij}(t)$ is heuristic function, α is the pheromone accumulated by the ant during its search process, β is the heuristic information, $p_{ij}^k(t)$ is the transition probability of ant K in city I of selecting J and $\tau_{ij}(t)$ is values of pheromone on the path connecting city I and city J.

The pheromone update rate for solving the multi-objective reconstruction is as follows:

$$\tau_i(t+n)=(1-\rho)\tau_i(t)+\Delta\tau_i(t)$$

$$\Delta\tau_j^k(t)=\begin{cases} Q/ploss^k(if \quad ant \quad k \quad select \quad road \quad j) \\ 0(otherwise) \end{cases} \tag{9}$$

Where ρ is the pheromone volatility rate, Q is a constant, $ploss^k$ is the active power of ant k.

The network found by the ant which finds the optimal solution in this iteration can be updated by:

$$\tau_{ij}^{'}(t+n)=\tau_{ij}(t+n)+Q^{'*}R_{ij}/Ploss_g \tag{10}$$

Where Q' and Q are both constants.

V. ILLUSTRATIVE EXAMPLES

A power plant with seven thermal units and one Wind Park is selected to test the above model based on ant colony algorithms. The load value in the next 24 hours is shown in Table 1. This is the quantity the power plant promise to supply. It is acquired by the power plant from the electricity futures market, short term electric power market and so on.

The forecasted wind park output in the next 24 ours is shown in Fig. 2.

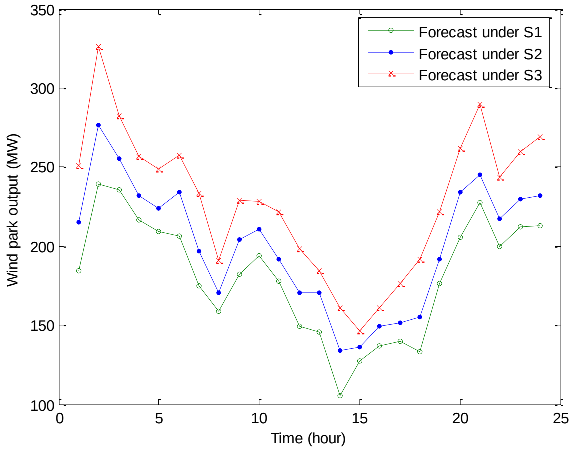

Figure 2. Wind power output forecast scenarios

the best scenarios S_1 (the largest wind power output) with a probability of 20%, the most likely scenarios S2 with a probability of 60% and the worst scenarios S_3 (the smallest wind power output) with a probability of 20%.

Table 3. The revenue comparison unit (Yuan)

Scenarios	**S_1**	**S_2**	**S_3**
Revenue under best dispatch plan (Yuan)	569562.07	564276.47	553492.65
Revenue under robust dispatch plan (Yuan)	562102.96	554658.69	545764.62
Difference	1.327%	1.734%	1.416%

When different values of risk factor θ are chosen, different values of expected revenue are obtained (Fig.3). The different values of the parameter of risk trade-off factor represent different degrees of management's risk aversion. We can observe from the graph in Fig. 3 that in general, the expected revenue decreases as the risk trade-off factor increases. When the risk trade-off factor is very large, the model results in zero wind power output dispatch. In other words, if the management is very conservative toward risk, the model will suggest that it get rid of all wind power consideration.

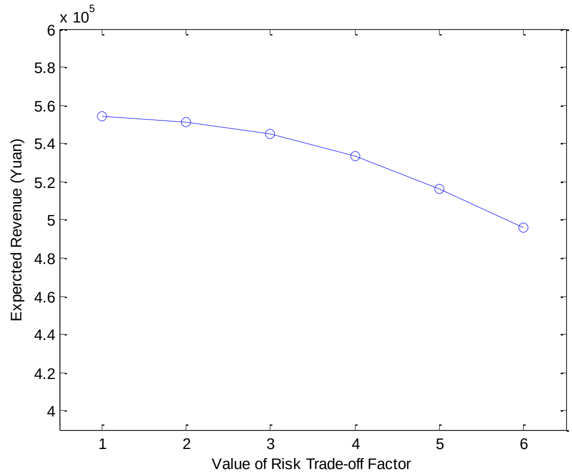

Figure 3. Relationship between expected revenue and risk trade-off factor.

VI. CONCLUSIONS

The concern for developing a low-carbon economic environment, the policy of reducing carbon emissions, developing wind power and other new energy sources have resulted in making energy management a more complex task. This paper presents the green revenue management model for a power plant with a wind park based on the idea of traditional energy management and revenue management. The stochastic characteristics of wind power, the spinning reserve of the thermal unit, the unit start and stop cost, and the external cost of emission are all considered in this model. The improved ant colony algorithm is used to solve the problem. The results show that this green revenue model can present a robust dispatch plan, which revenue will be always near the optimal solution no matter how the wind power output scenario changes.

Also the Decision-makers' risk aversion is considered in the objective function. When the risk trade-off factor is very large, the model results in zero wind power output dispatch. In other words, if the management is very conservative toward risk, the model will suggest that it get rid of all wind power consideration.

This model is helpful for the safe and reliable running of the power plant with wind parks. It is of great significance for the economy and environmental benefits.

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Dr. Qian Zhang Ph.D in School of Economics and Management North China Electric Power University, Baoding China. The main research new energy revenue management.