# Multi-objective Unit Commitment Model on Wind power Accommodation and Flexible Load Response

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**Abstract:** Unit commitment is an important aspect of optimal operation of power system. In this paper, the wind power accommodation and flexible load response are proposed to evaluate unit commitment problems. Based on the evaluation functions, the optimization of unit commitment problems is translated into constraints multi-objective optimization problem. These objectives are modeled with a differential evolution algorithm with self-adaptive improved strategies method to evaluate their imprecise nature. The model and algorithms are applied to calculate a case of 10 units. It is shown that the system needs to have more spinning reserve and increase the peak regulation capacity of each time period. The results show that the proposed modeling method can provide a useful guidance for unit commitment problems

## 1. Introduction

Unit commitment is an important aspect of optimal operation of power system. The UC problem has commonly been formulated as a nonlinear, large scale, mixed-integer combinatorial optimization problem with constraints. The exact solution to the problem can be obtained only by complete enumeration, often at the cost of a prohibitively large computation time requirement for realistic power systems [1]. For the characteristic of randomness, fluctuation and intermittence, as well as the influence that wind power would bring to frequency regulation, system reserve and operation mode of other units, the traditional method has not a good solution to the problem of transmission system planning with large scale wind power integrated[2].

When the demand response participates in the economic scheduling, the optimal decision variables, the objective functions and the constraints are different for the different participating users and the different scheduling methods. Flexible Load Response (FLR) is the main research direction, which is usually divided into interruptible load response and incentive load response [3-5]. A stochastic model is introduced for evaluating the impact of integration of large amounts of intermittent wind power [6]. A security-constrained unit commitment algorithm which takes the intermittency and volatility of wind power generation into account is presented [7]. The stochastic unit commitment problem is usually solved using deterministic unit commitment algorithms. Some solution techniques have been proposed such as heuristics, dynamic programming, mixed- integer linear programming. Lagrangian relaxation, simulated annealing, and evolution- inspired approaches [8]. A recent extensive literature survey on unit commitment can be found in [9]. MILP and LR are the most widely used to solve the unit commitment problem opens up many opportunities to deal directly with a number of constraints and models that tend to be very difficult to implement with the LR formulation. These include modeling of combined cycle plants, hydro unit commitment, for bidden zones, multi-area and zonal constraints, ancillary service markets, and many more [10-14].

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## 2. Mathematical Model of Unit Commitment on Wind Power Capability and System Cost

As the scale of development and construction of wind power continues to expand, enhance the capacity of wind power utilization is becoming increasingly prominent. The expression of Wind Power Capability is shown in $\alpha_W$. In this function, $Q_d^{w,c}$ is abandoned day wind power, $\alpha_W$ is the rate of abandoned wind power:

$$\alpha_W = \sum Q_d^{w,c} / \sum Q_d^{w} \tag{1}$$

$$Q_d^{w,c} = \sum_{t=1}^{T} P_{d,t,m}^{W,C} \tag{2}$$

$$P_{d,t,m}^{w,c} = P_r(E_0) * (P_{d,t,m}^{w} - P_{t,m}^{w,s}) \tag{3}$$

$$P_{t,d,m}^{w,s} = P_{t,d,m}^{L} - P_{\min,d,m}^{G} \tag{4}$$

Where $t$ represents various time intervals at typical day, $T$ is the number of period of days , month m, $L$ represents the load ,$W$ represents wind power. $S$ represents receiving space. $P_{t,d,m}^{w,s}$ is each period space to accommodate wind power, $P_{\min,d,m}^{G}$ is minimum system power output. $P_{t,d,m}^{L}$ is sequence in time curve, $Q_d^{w}$ is day generated electrical energy without abandoned wind power, $P_r(E_0)$ is the probability of occurrence of an event.

The generation cost includes the conventional generation cost and the flexible load cost. The conventional cost $GC_{Gt}$ includes the fuel consumption cost of thermal power units and the cost of wind power generation. The cost of the flexible load includes the $GC_{It}$ of the interruption load and the incentive load cost $GC_{Ht}$

The flexible load is divided into an interruptible load and an excitation load, and the flexible load cost includes a compensation cost of the interruptable load and an excitation cost of the excitation load. In this paper, when the flexible load is used, the user obtains the electricity price compensation and the carbon emission right compensation. Therefore, the specific formula of the flexible load cost is

$$GG_W = \left\{ GC_{Gt} + GC_{It} + GC_{Ht} \right\} \tag{5}$$

$$GC_{Gt} = \sum_{t=1}^{T} \left( \sum_{i=1}^{NG} C_{Gi}(P_{Gi}^{t}) + \sum_{j=1}^{Nw} Cw(P_{wi}^{t}) \right) \tag{6}$$

$$GC_{It} = \sum_{t=1}^{T} \left\{ \sum_{i=1}^{NI} [S_{Ij}^{t}(\rho_1(P_{Ii}^{t})^2 + \rho_2 P_{Ii}^{t} - \rho_2 P_{Ii}^{t}\omega_{Ii}) + C_1 \varpi P_{Ii}^{t}] \right\} \tag{7}$$

$$GC_{Ht} = \sum_{t=1}^{T} \left\{ \sum_{i=1}^{NH} [S_{Hi}^{t}(\eta_1(P_{Hi}^{t})^2 + \eta_2 P_{Hi}^{t} - \eta_2 P_{HI}^{t}\omega_{HI}) + C_2 \varpi^{-1} P_{Hi}^{t}] \right\} \tag{8}$$

Where, $N_I$ is the number of users that can interrupt the load; $N_H$ is the number of users that motivate the load of the system; $S_{Ij}^{t}$ is the state vector of interrupt load user, $\rho_1$ and $\rho_2$ are

compensation Coefficient; $S_{ffk}^{t}$ indicates the load of the user K; $P_{ffk}^{t}$ is the capacity vector of the incentive load, and the incentive system is the incentive to load the load users.

The wind power accommodation capacity cannot be simply defined as accessible wind power. The pure maximization problem of accessible wind power is described. In order to integrate the different objective and get an authentic accommodation capacity, the models are combined to a synthesized multi-objective UC optimization problem considering wind power accommodation capacity and Cost. The constraints of this model mainly include:

Active power balance of power system:

$$\sum_{k=1}^{NG} P_{gk}(t) - P_{abd}(t) = P_L(t) \tag{9}$$

Upper and lower limits of unit output

$$u_{gt} \cdot P_{k,\min} \le P_{gk}(t) \le u_{gk} P_{k,\max} \tag{10}$$

Spinning reserve limit of the system

$$P_L(t)(1+S_R) \le \sum_{k=1}^{N_G} u_{gk}(t) P_{k,\max} \tag{11}$$

Minimal on/off time duration

$$T_{gk}^{on}(t) \ge T_k^{up}; T_k^{down} \le T_{gk}^{off}(t); \tag{12}$$

Ramp rate limit

$$|P_{gk}(t) - P_{gk}(t-1)| \le u_{gk}(t) P_k^{ramp} \tag{13}$$

In these constraints, $S_R$ is the spinning reserve; $T_k^{up}$ and $T_k^{down}$ is the minimal on/ off time duration; $T_{gk}^{on}(t)$ and $T_{gk}^{off}(t)$ is the accumulated on/off time duration.

## 3. Unit Commitment Multi-objective optimized model based on Differential Evolution Algorithm

Based on the evaluation functions, the multi-objective optimization model is constructed to maximize the satisfactions of different objectives by adjusting Unit Commitment. The multi-objective optimization model is represented as:

$$\begin{aligned}
&Min(Mep(\alpha_W), Mep(GC_W)) \\
&Subject \\
&\begin{cases}
\sum_{k=1}^{NG} P_{gk}(t) - P_{abd}(t) = P_L(t) \\
u_{gt} \cdot P_{k,\min} \le P_{gk}(t) \le u_{gk} P_{k,\max} \\
P_L(t)(1+S_R) \le \sum_{k=1}^{N_G} u_{gk}(t) P_{k,\max} \\
T_{gk}^{on}(t) \ge T_k^{up}; T_k^{down} \le T_{gk}^{off}(t); \\
\sum_{i=1}^{N} P_i - P_L + (P_{PV} + P_{WT} + P_{hydl}) = 0 \\
|P_{gk}(t) - P_{gk}(t-1)| \le u_{gk}(t) P_k^{ramp}
\end{cases}
\end{aligned} \tag{15}$$

The aim of a power system multi-objective optimization is find a solution, In this formula, $Mep(\alpha_W), Mep(GC_W)$ is objective function, The aim of a power system reconfiguration optimization is to find a solution, in formula (15), constraint function is very complex. The problem is a global optimization problem, namely, covariance matrix adaptation evolution strategies, differential evolution. In general, the faster convergence leads to local optimum, it can be overcome by using a

larger population size. In this paper, we present the Self-Adaptive Differential Evolution Algorithm with Improved Strategies (SDEI) to solve the problem. SDEI has extended from the original algorithm of DE. The basic operations are illustrated as follows.

The SDEI structure is a parallel search algorithm. It uses N vectors of the decision parameters. There are four operators for the algorithm, namely, mutation, crossover, selection and migrating in order to obtain more accurate approximations.

Stage1. The initial population $X_0^i$ is selected randomly and it covers the entire search space uniformly:

$$X_0^i = X_{\min} + \rho_i (X_{\max} - X_{\min}) \tag{16}$$

Where i=1,2….N. $\rho_i$ is a uniformly distributed random number. $X_{\max}$ is the lower bound and $X_{\min}$ is upper bound of the decision parameters.

Stage2. For each i = 1. . . N, a new mutant vector $V_{G+1}^i$ is generated by combining vectors from the current population. A mutant individual $V_{G+1}^i$ is generated according to the following equations

$$V_{G+1}^i = X_G^{best} + \mu (X_G^{r1} - X_G^{r2}) \tag{17}$$

where $X_G^{best}$ denotes the best individual; $\mu > 0$ is mutation constant parameter, which controls the difference amplification between two individuals; and r1, r2∈ {1, 2, . . . , N}. An adaptive setting rule shows in (18)

$$t = e^{1-\frac{N_m}{N_m+1-N}} \tag{18}$$

$$\mu = \mu_0 * 2^t \tag{19}$$

Where, $\mu_0$ is initial mutation operator. N indicates the current evolution number. $N_m$ denotes the maximum fitness evaluation number . At the beginning, the adaptive mutation operator is carried out with a probability within [ $\mu_0$ -2 $\mu_0$ ] to maintain the diversity. Along with the evolution lapse, Mutation operators are gradually reduced to retain good information and expect good balance.

Stage3. In order to increase next population diversity, an offspring is reproduced by the crossover operation. For j = 1, 2… n, a random number rand1 ∈ [0, 1] is generated.

If rand1 is smaller than the predefined crossover constant, $CR \in [0, 1]$, the jth mutant vector becomes the jth trial vector component $V_{G+1}^i$. Otherwise, the jth target vector $X_G^{ij}$ is selected as the jth trial vector component.

$$U_{G=1}^i = (u_{G+1,}^{i1} u_{G+1,}^{i2} \ldots\ldots u_{G+1}^{in}) \tag{20}$$

$$u_{G+1}^{ij} = \begin{cases} v_{G+1}^i & if \quad rand1 \le CR \quad or \quad j = rnbr(i) \\ x_G^{ij} & if \quad rand1 > CR \quad or \quad j \ne rnbr(i) \end{cases}$$

Where $rnbr(i)$ is a randomly chosen index ∈ {1.2.3..n}. $rand1$ is the jth uniform random number generator evaluation ∈ [0, 1].

Stage4. At the selection step, the crossover trial vector is used for the next generation, only when the target function value decreases with respect to the previous vector,

$$X_{G+1}^i = \begin{cases} U_{G+1}^i & if \quad R(U_{G+1}^i) > R(X_G^i) \\ X_G^i & otherwise \end{cases} \tag{21}$$

Stage5. However, faster descending usually brings a local minimum or the next better individuals are not reproduced by the mutation and crossover operations to clustered individuals.

New population can be regenerated by the migrating operation. The new candidates are chosen based on the best individual $X_{G+1}^{i}$.The jth gene of the ith individual is therefore regenerated by.

$$X_{G+1}^{j} = \begin{cases} X_G^{best} + rand2_{ij}(X_G^{\min} - X_G^{best}) & if\ \overline{rand2} \geq \dfrac{X_G^{best} - X_G^{\min}}{X_G^{\max} - X_G^{\min}} \\ X_G^{best} + rand2_{ij}(X_G^{\min} - X_G^{best}) & otherwise; \end{cases} \quad (22)$$

Where $rand2_{ij}$, $\overline{rand2_{ij}} \in [0, 1]$ is the jth uniform random number generator evaluation, $X_G^{\min}$ and $X_G^{\max}$ are the lower and upper bounds of the jth decision parameters gene. Only if population diversity matches the desired tolerance, The migrating operation is performed. The measure $\rho_m$ is defined as,

$$\rho_m = \frac{\sum_{i=1}^{N}\sum_{j=1}^{n}\eta_{ji}}{n(N-1)} < \varepsilon_1 \quad (23)$$

Where $\eta_{ji} = \begin{cases} 1, if \left|(X_G^{i} - X_G^{best}) / X_G^{best}\right| > \varepsilon_2 \\ 0 \quad otherwise \end{cases}$

Where $\varepsilon_1$ and $\varepsilon_2$ are the desired tolerance for the population and the gene diversity to the best individual. Here, $\eta_{ji}$ is a gene diversity index. Zero means that the jth gene closely clusters to the best individual. If population diversity degree is smaller than the tolerance $\varepsilon_1$, the migrating operation is performed.

## 4. Case Study

A 10 unit system is used for testing the proposed algorithm considering the uncertainty of wind power generation. The system is transformed into a suitable case of 10 units and 34 buses to test the proposed models and algorithms. The data of the 10- unit system is provided. Table1give parameters of 10 unit, including $P_{gk,\min}$, $P_{gk,\max}$, $TK_{up}$, $TK_{down}$, Initial $P_{gk}$, State hours are shown in table1, Wind power and load data in 24 hours shown in table2. The model has been implemented on a PC with the AMD Socket AM2 and 2G RAM memory using Linux and Java to solve the proposed formulation.

Table 1. Parameters of 10 units

| Unit | $P_{gk,\min}$ | $P_{gk,\max}$ | $TK_{up}$ | $TK_{down}$ | Initial $P_{gk}$ | State hours |
|---|---|---|---|---|---|---|
| 1 | 5 | 30 | 1 | 0 | 5 | 1 |
| 2 | 5 | 30 | 1 | 0 | 5 | 1 |
| 3 | 5 | 30 | 1 | 1 | 5 | 1 |
| 4 | 150 | 300 | 8 | 8 | 150 | 8 |
| 5 | 100 | 300 | 2 | 8 | 100 | 8 |
| 6 | 10 | 30 | 1 | 1 | 10 | 1 |
| 7 | 8 | 20 | 1 | 0 | 8 | 1 |
| 8 | 25 | 50 | 2 | 2 | 25 | 2 |
| 9 | 25 | 100 | 5 | 5 | 25 | 5 |
| 10 | 25 | 100 | 1 | 5 | 25 | 5 |

Table 2. Wind power and load data in 24 hours

| | Wind power rate | Load data rate |
|---|---|---|
| 1 | 0.8 | 0.8 |
| 2 | 0.9 | 0.81 |
| 3 | 0.68 | 0.82 |
| 4 | 0.74 | 0.8 |
| 5 | 0.5 | 0.83 |
| 6 | 0.36 | 0.81 |
| 7 | 0.57 | 0.86 |
| 8 | 0.67 | 0.85 |
| 9 | 0.80 | 0.87 |
| 10 | 0.83 | 0.86 |
| 11 | 0.81 | 0.8 |
| 12 | 0.87 | 0.81 |
| 13 | 0.66 | 0.82 |
| 14 | 0.75 | 0.8 |
| 15 | 0.4 | 0.83 |
| 16 | 0.35 | 0.81 |
| 17 | 0.52 | 0.86 |
| 18 | 0.64 | 0.85 |
| 19 | 0.81 | 0.87 |
| 20 | 0.81 | 0.86 |
| 21 | 0.57 | 0.83 |
| 22 | 0.36 | 0.81 |
| 23 | 0.54 | 0.86 |

Tables 3 present the results obtained using the algorithm proposed in this paper for different sets of UCP instances. The simulation evaluates Unit Commitment Multi-objective optimized model from two aspects: rate of abandoned wind power and cost, rate of abandoned wind power represents the wind power accommodation capacity, We also give out Optimization abandon wind rate. Max abandon wind rate, Max cost. It is shown that maximum abandon wind rate is 6.61, and maximum Cost is 163.275 , it is show that the system need to have more spinning reserve and increase the peak regulation capacity of each time period.

Table 3. Wind power and Cost data

| | Optimization abandon wind rate | Optimization Cost | Max abandon wind rate | Max Cost |
|---|---|---|---|---|
| 1 | 0.9 | 122.275 | 6.61 | 163.275 |
| 2 | 0.86 | 116.763 | 4.59 | 156.356 |
| 3 | 0.78 | 114.783 | 6.53 | 153.788 |
| 4 | 0.74 | 113.435 | 4.21 | 149.536 |
| 5 | 0.72 | 103.789 | 0.79 | 133. 893 |
| 6 | 0.69 | 100.637 | 0.73 | 130. 368 |
| 7 | 0.67 | 109.667 | 0.72 | 139.852 |
| 8 | 0.65 | 110.472 | 0.822 | 140. 899 |
| 9 | 0.58 | 110.435 | 0.67 | 138.987 |
| 10 | 0.52 | 118.217 | 2.61 | 143.268 |
| 11 | 0.5 | 117.763 | 3.51 | 147.853 |
| 12 | 0.47 | 119.662 | 3.59 | 159.697 |

## 5. Conclusions and directions for future work

The UC problem has commonly been formulated as optimization problem with constraints. In this paper, the cost of Flexible Load Response is proposed in system operation cost, as a whole and establishes the mathematical model. We have proposed a differential evolution algorithm with self-Adaptive improved strategies for unit commitment problems. A 10 unit system is used for testing

the proposed algorithm considering the uncertainty of wind power and cost. The simulation results show that the system needs to have more spinning reserve and increase the peak regulation capacity of each time period.

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