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Unit Commitment in Wind Farms based on a Glowworm Metaphor Algorithm

J. Yan, J. Zhang, Y. Liu, S. Han, L. Li, C. Gu

***Abstract*—Mechanical health and operational efficiency of a wind turbine (WT) are important to the overall cost effectiveness in a wind farm. This paper presents a unit commitment (UC) model based on fatigue damage modeling of blades and uncertainty estimation of wind power forecasting (WPF). A novel glowworm metaphor algorithm (GMA) is developed to solve the proposed UC problem. During the pheromone updating of GMA, the luminescence carrying by glowworm reflects the net improvement by agent moving. This characteristic supports GMA to find the global optima to optimization of UC problem. The proposed UC objective is minimizing the mechanical damages of WTs in the whole wind farm. Uncertain interval of wind power generation is obtained as constraint function based on relevance vector machine (RVM). Data from a wind farm in China are used to validate the feasibility and effectiveness of the proposed method. Simulation results reveal the capabilities of GMA to efficiently get the better performance than benchmark methods, in terms of minimum mechanical damage, reliability and running efficiency. The benchmark methods are particle swarm optimization (PSO) and genetic algorithm (GA). The comparison between UC with and without consideration of WPF uncertainty exhibits the superiority of the incorporation of WPF uncertainty modeling.**

***Index Terms*—blade fatigue damage value, glowworm metaphor algorithm, maintenance cost, wind farm, wind power forecasting, uncertainty estimation.**

I. Introduction

Unit commitment (UC) in a wind farm is to determine the day ahead start-up/shut-down schedules of WTs in each operation timeslot. The goal is to minimize the wind power generation cost while satisfying the constraints of system demand and wind availabilities, etc. As the increase of wind farm scale and wind turbine (WT) capacity, UC is getting more difficult challenges to solve. This comes from the scaling-up uncertainty from wind intermittency and computational burden on operation. Moreover, the large scale WTs bear more fatigue effects from variable wind, frequent on/off operation etc., and thereby bringing down their lifespan [1]. It is significant to improve traditional operation strategy in wind farms, in terms of mechanical damages of WTs, profitability for wind farm owners, operation efficiency and quality of wind power output [2][16].

Most of the early works on the UC problem use deterministic wind power forecasting (WPF) [9-11]. However, the root square mean error (RSME) of a day-ahead WPF can be as high as 20% of the wind farm capacity and even larger in extreme conditions. When a large-scale wind farm is considered, the wake effect or topographical effect make wind power even harder to predict. Therefore, many works consider forecasting uncertainties during operating wind farms using scenario constructing method [5], fuzzy set theory [6] or stochastic programming [7,8]. Kalantari proposed security constrained unit commitment (SCUC) based on multiple stochastic wind power scenarios to account for wind power uncertainty, and improved the computational efficiency; and the proposed SCUC is reformulated within the loadability set rather than on the larger set of generation and demand [5]. In paper [6], the 24 hours ahead load forecasting uncertainty was evaluated by applying fuzzy set theory and added to the multi objective UC model; this UC is to minimize both the supply risk and the generation cost. Wang formulated a stochastic price-based UC problem with chance constraints to ensure wind power utilization considering price and wind power forecasting uncertainties; and solved the optimization problem by sample average approximation method [7].

All the above UC optimizations are commonly with high dimensional, nonlinear and mixed integer combinatorial problem. Many mathematical programming and heuristic based approaches have been utilized to solve the UC problem, for instance, dynamic programming, neural networks, simulated annealing, evolutionary programming, constraint logic programming, genetic algorithms (GA), Lagrangian relaxation, tabu search and particle swarm optimization (PSO) [12-16]. However, these methods might bear additional computational burden or even suffer from "dimensional curve", particularly when high dimension mathematical model for a large-scale wind farm with hundreds of WTs or wind farm cluster is concerned.

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With the intention of developing better algorithm to solve optimal operation problems, a new searching theory-glowworm metaphor algorithm (GMA) is proposed by Krishnanand and Ghose [24]. GMA has been applied for sensor deployment in wireless sensor networks []. The results prove that GSO outperforms PSO.

This paper presents three means of improving traditional UC within wind farms: 1) a wind farm damage related unit commitment model is established based on blade fatigue damage; 2) glowworm metaphor algorithm (GMA) to solve the mechanical damage minimizing UC problem; and 3) quantification of WPF uncertainties in a UC formulation based on wind power interval forecasting. Based on the case study in a Chinese wind farm, it can be concluded that GMA approach is reliable and efficient in solving UC problem. The proposed the mechanical damage minimizing objective and uncertainty incorporated-UC model can diminish the maintenance cost and extend wind turbine lifespan in wind farms.

The reminder of the paper is organised as follows. In section II, the model for calculating fatigue damage values of the blades (FDVB) in four operational conditions are firstly established to quantify the mechanical losses of WT. With fatigue model, the objective of UC problem can be established in section III. Also in section III, the uncertainty interval of wind turbine generation forecasting are estimated and incorporated into the UC constraints. In section 4, GMA theory is applied to solve the optimization problem. In section 5, a wind farm in China is taken as case study to validate the proposed GMA approach and UC model; and to compare the performance to benchmark methods – PSO and GA. Conclusions are drawn in section VI.

II. Fatigue Damage Value of Blades (FDVB)

Blades are important and fragile component for WTs to convert wind energy into mechanical energy. From the economic perspectives, blade take up to 20% of the total cost of WTs [3]. Its maintenance cost is at least 5% of the total O&M cost for a WT in healthy conditions [4]. This cost goes much higher if the blades are in malfunction due to frequent operational motions. And, the profits of wind farms will be slashed. From the mechanical damage perspectives, wind loads on a WT are mostly born by blades, especially the root part of blades, and then transferred to the interconnection piece, rotor and hub. This mechanical damage potentially reduces the economic efficiency of wind farm operation or even restricts the wind power share in a power system. Therefore, it is significant to incorporate blade damage consideration in maintenance and operation strategy, especially under the context when the installation capacity of wind farm is constantly increasing.

Many studies focus on the fatigue behavior of wind turbine blades [25-26]. However, none of these works quantifies damaging model of blades in UC problem. So, the maintenance cost from the mechanical damages of a WT is not considered in many previous works, although it is the primary capital flow during running a wind farm.

A. Therefore, it is significant to improve the traditional UC models to incorporate mechanical damage formulations for reducing the total costs of operating and maintaining all WTs in a wind farm. In this section, the fatigue damage value of blades [17] indicating the lifetime and damages of WTs is calculated based on Miner cumulative fatigue damage theory [18].WT Working Conditions

The framework of deciding the fatigue damage value is given in Fig.1. First, four typical loading conditions are defined for simulating various working conditions of WTs, according to Load Assumptions in GL2003 standard released by Germanischer Lloyd (GL) [19]. Various operational conditions of WTs are considered because different external factors have variable loading effects. For example, when WTs operate in a normal generation state with normal wind conditions, particularly operating in rated power generation state, the load or damage on blade root is relatively small, while impulse loads would increase the blade damage when operating yawing or braking process. Second, based on the modeling of blade fatigue load in typical operational conditions, loading and cycling number are calculated to establish the fatigue load spectrum of blades. And then, fatigue damage value can be calculated based on miner cumulative fatigue theory.

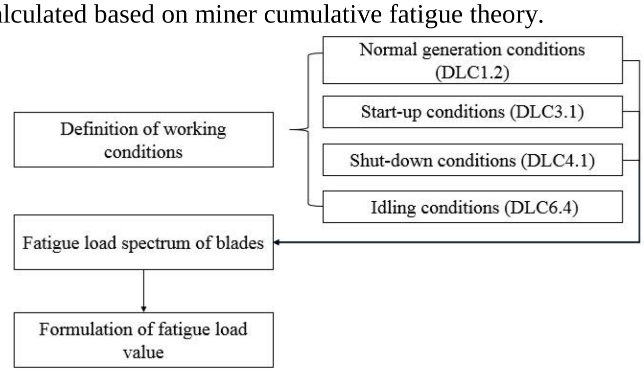

Fig.1 The framework of deciding fatigue damage value

(i) Normal generation conditions (DLC1.2): Normal turbulence model -NTM are set under different average wind speed ranging from $V_{in} < V_{hub} < V_{out}$ (V_{in}: cut in wind speed; V_{hub}: wind speed at hub height; V_{out}: cut off wind speed) to calculate shimmy moment of blade root with various wind conditions;

(ii) Start-up conditions (DLC3.1): Normal wind profile model-NWP are set to calculate shimmy moment under different stable wind speed ranging from $V_{in} < V_{hub} < V_{out}$;

(iii) Shut-down conditions (DLC4.1): Normal wind profile model-NWP are set to calculate shimmy moment under different stable wind speed ranging from $V_{in} < V_{hub} < V_{out}$;

(iv) Idling conditions (DLC6.4): Normal turbulence model -NTM are set under different average wind speed to calculate shimmy moment of blade root with various wind conditions.

B. Fatigue Load Spectrum of Blades

After defining four typical working conditions, the fatigue load spectrum of blades can be calculated based on GH-Bladed software. Fatigue load spectrum describes the relationship between cycling times and loading. It is the basics for analyzing the loading conditions and forecasting of fatigue lifetime [20-21].

With GH-Bladed, the external environment and operational states of WTs can be simulated. In this way, the cycle counts and the loads at blades root under diverse working conditions can be achieved. The loading models in GH-Bladed load module are classified into steady loads, cyclic loads and transient load.

- Steady load arises from turbulence wind field with certain mean wind speed;
- Cyclic load arises mainly from wind shear effects, yawing, tower-shadow effects, etc;
- Transient loads are primarily from start-on, shut-down of WTs, etc.

The occurrence times of steady and cyclic loads under given load level can be calculated from wind speed frequency distribution (typically Weibull distribution) or designing WT lifespan. As for transient load, it can be determined from GL standard.

C. Miner Cumulative Fatigue Theory

Components in WTs bear multitudinous cyclic loads with changing magnitude. This fatigue effect cumulates and causes equipment failure. Miner theory is commonly-accepted linear cumulative fatigue theory to quantify accumulative fatigue damage, which neglects the influence from loading sequence on the total damage value. Miner theory assumes that: i) different loads are assumed to be independent from each other; ii) when cumulative damage value reaches a given ceiling limits, components or equipment would be damaged.

Assumed that the load magnitude born by WT components is S_{a1}; total cycling number is N_1, also termed as fatigue lifetime. The total damage amounts suffered during the whole running life are linearly allocated to each cycling process. So, damage value in each cycling process can be written as $D_1 = 1/N_1$. If load magnitude is S_{a1} and it happens n_1 times, the corresponding component damage value is D_1. When $\sum (n_i / N_i) = 1$, the whole damaging process is finished and the component damages with fatigue loads. n_1 is the cyclic counts under given cyclic load; N_i is the total lifetime under given load level. Therefore, fatigue damage value (FDV) can be defined as eq.(1) under various WT operating conditions.

$$D_i = \frac{n_i / N_i}{h_i} \tag{1}$$

where, i represents given WT working condition; n_i is cyclic counts under i working condition; N_i is total cyclic number under i working conditions; h_i is running time or numbers of start-up/shut-off under i working conditions; n_i is relative damage value per minute under i working conditions.

III. Unit Commitment Formulation

In this section, the established fatigue damage model is firstly integrated in the objective formulation of the UC problem. Secondly, we extend our previous work on forecasting uncertainty modeling and incorporate it in the UC constraints. Therefore, the tradeoff between maximizing all available wind energy and minimizing total damage costs in the UC model can be represented to improve the economic efficiency of wind farms.

A. Objectives

To take full advantage of all available wind energy, WTs might need to operate frequently (for instance start up, shut down, yaw) according to the current wind availabilities. However, the mechanical damages during frequent operation might increase as well as the maintenance costs. In the proposed UC model, the mechanical damage of blades and absorption of all available wind energy are tradeoff to maximize the profits of the whole wind farm.

The objective of the proposed UC problem is shown in eq.(2). The first item is the damage during normal running state. The second and third items are damages during start-up and shut-off, respectively. It aims to achieve the minimum damage of blades in a whole wind farm within the constraints of both wind availabilities at each WT location and demand in power systems.

$$\begin{aligned} \min F = & \sum_{j=1}^{T}\sum_{i=1}^{N}\left(x_{i,j}u_{i,j} \bullet t\right) + \\ & \sum_{j=1}^{T}\sum_{i=1}^{N} y_{i,j}u_{i,j}\left(1-u_{i,j-1}\right) + \sum_{j=1}^{T}\sum_{i=1}^{N} z_{i,j}, u_{i,j-1}\left(1-u_{i,j}\right) \end{aligned} \tag{2}$$

where, F represents the total damage value of blades. $x_{i,j}$, $y_{i,j}$ and $z_{i,j}$ are mechanical damage of the i^{th} WT at j^{th} period when WT operates in normal running state, start-up state and shut-down state, respectively. $u_{i,j}$ presents start or stop state of the i^{th} WT within the j^{th} time slot, and it is a binary variable. 0 indicates shut-down state, while 1 represents operation state. t is the operation time period of WTs. T is dispatching times. N is the total number of WTs.

B. Constraints

Different from conventional and hydro power plants, wind farm operators have neither fuel cost curves for thermal generators nor flow control curves for hydropower generators to make day-ahead dispatching schedules. The only information about wind power for unit commitment is wind power forecasting curves for a wind farm or each single WT. Inevitably, forecasting error incurs negative uncertain and risky effects on decision making.

In our prior paper [22-23], wind power interval forecasting model is established based on a statistical model termed as relevance vector machine (RVM). It provides not only single forecasting value but also uncertain ranges of power output under given confidence levels. It was proved that RVM has better performance compared to artificial neural network (ANN) and support vector machine (SVM) algorithm in a deterministic and probabilistic manner. Wind power interval forecasting helps ease the difficulty of integrating WPF uncertainties to UC and reduces uncertainty and variability in wind power operating.

eq.(3) is the power generation constraints based on RVM wind power interval forecasting model.

$$P_{i,j,\min} \le P_{i,j} \le P_{i,j,\max} \tag{3}$$

where, $P_{i,j,\max}$ and $P_{i,j,\min}$ are the upper and lower power output limit of the i^{th} WT under certain confidence level at j^{th} period. $P_{i,j}$ is the scheduled power output of the i^{th} WT at j^{th} period.

The power balance constraint is as eq.(4).

$$\sum_{i=1}^{N} u_{i,j} P_{i,j} - P_{Dj} - P_{Lj} = 0 \tag{4}$$

where, N is the number of WTs; $u_{i,j}$ is the state of the i^{th} WT during the j^{th} period. P_{Dj} is the planning output for wind farm at j^{th} period and it meets the dispatching command of power system. P_{Lj} is the line losses of electrical collector system in wind farm at j^{th} period.

The line losses of electrical collector system in wind farm is assumed as 7% of the total system load, as constraint shown in eq.(5). So, the spinning reserves is as eq.(6).

$$P_{Dj} + P_{Lj} = 1.07 P_{Dj} \tag{5}$$

$$\sum_{i=1}^{N} u_{ij} P_{\max} \ge 1.07 P_{Dj} \tag{6}$$

IV. Optimization with Glowworm Metaphor Algorithm (GMA)

Glowworm metaphor algorithm [24] is a novel optimization technique and it is a variant of a well-known ant colony optimization (ACO). Glowworms or particles in GMA are initially distributed randomly in the solution space carrying with equal luminescence quantity. Each glowworm moves within the local decision range and changes its moving direction towards the "brighter" neighbor, whose luminescence quantity is higher than its own. If the number of neighboring glowworms is low, the local decision range is enlarged in order to find more neighbors; otherwise the range is reduced. In fact, the decision domain range of GMA varies as a function of the neighbor density. It therefore improves the optimization performance in terms of maximizing the number of peaks detected.

The main steps of implementing GMA algorithm in UC optimization problem are introduced as follow, with the flowchart given in Fig.2.

(1) Preparation of samples

Interval forecasting results from RVM model are obtained, including deterministic wind power output, upper and lower bounds of wind power output at each time slot. Load demands from power system operators are also imported.

(2) Initialization of GMA

Each glowworm, whose value indicates the state of each WT, is randomly dispersed in the workspace with equal initialized quantity of luminescence. "1" represents the WT is in "on" state; "0" represents the WT is in "stop" state. n is the number of glowworms (WTs).

(3) Calculation of fitness function

Fitness function shows the merits and demerits of individual glowworm or their solutions. In GMA, the greater the luminescence value is, the more optimal the glowworm is. In this paper, fitness function is presented as the reciprocal of objective function.

$$J_j(t) = 1/F \tag{7}$$

where, $J_j(t)$ is the fitness function at time t; F is objective function.

(4) Luminescence update phase

Glowworms start with equal luminescence value and update their luminescence according to each glowworm fitness value at their current position. The updating rule of glowworm is given by:

$$\tau_j(t+1) = \max\{0, (1-\rho)\tau_j(t) + \gamma J_j(t+1)\} \tag{8}$$

where, ρ is the luminescence decay constant $(0<\rho<1)$; γ is the luminescence enhancement constant, being proportional to the luminescence; $J_j(t)$ is the objective function value of j^{th} glowworm or WT at time of t.

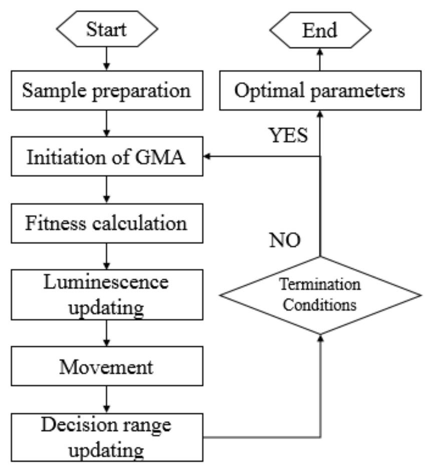

Fig. 2 Flowchart of GMA

(5) Movement phase

Each glowworm (WT) identifies a set of neighbors using following rules in eq.(9).

$$N_i(t) = \{ j : d(i,j,t) < r_d^i(t); \tau_i(t) < \tau_j(t) \},\ j \in N_i(t) \tag{9}$$

where $N_i(t)$ is a set of neighbors for the i^{th} glowworm (or WT) at time t; $d(i,j,t)$ is the Euclidian distance between WT i and WT j; $r_d^{\,i}(t)$ is the local decision range value of WT i at time t and it is bounded by the radial range of the luminescence sensor r_s; $\tau_j(t)$ is the luminescence level associated with WT j at time t.

And then, glowworms identify a brighter neighbor (with larger luminescence value) using probabilistic mechanism. For each WT i, the probability of moving towards a neighbor j

$p_j(t)$ is calculated using eq.(10).

$$p_j(t) = \frac{\tau_j(t)}{\sum_{j \in N_i(t)} \tau_j(t)} \tag{10}$$

(6) Decision domain updating

The local decision range of each WT is updating by

$$r_d^i(t+1) = \frac{r_s}{1+\beta D_i(t)} \tag{11}$$

where, $D_i(t) = \frac{N_i(t)}{\pi r_s^2}$ is the neighbor density of WT i at time t ; β is a constant parameter.

V. Case Study

Data from a wind farm in North China is used to validate the proposed model. There are 33 1.5MW doubly-fed induction wind turbines installed and the total installed capacity is 49.5 MW. Within the operating period, demand constraints at each time slot are assumed to be 16,000 kW, 16,000 kW, 20,000 kW, 20,000 kW, respectively. The numerical simulation is carried out in GH-Bladed 3.81 for fatigue damage modeling, and Matlab b2011 is the platform for unit commitment using GMA to search for a target of minimum total mechanical damage in the wind farm. Yawing error is set to be ± 8 °, and safety factor is 1.0.

A. Fatigue Damage Analysis

The loads at blade root under four working conditions with cut-in wind speed (3.5 m/s), rated wind speed (9 m/s) and cut-off wind speed (25m/s) are shown in Fig.3-14.

(1) Normal generation conditions (DLC1.2). It is clear to see that the loads in three conditions are changing cyclically, especially under cut-in and rated wind speed. Besides, the load amplitudes and its fluctuation frequencies increase with the growth of mean wind speed.

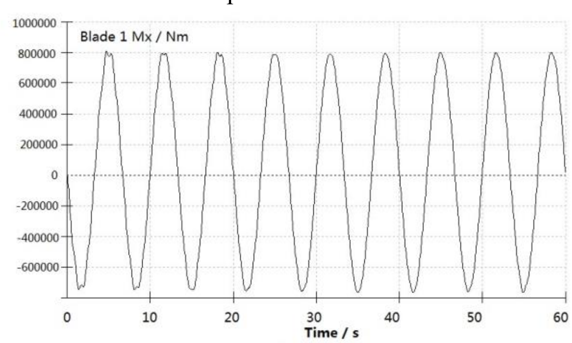

Fig. 3 Loads when wind speed is 3.5m/s

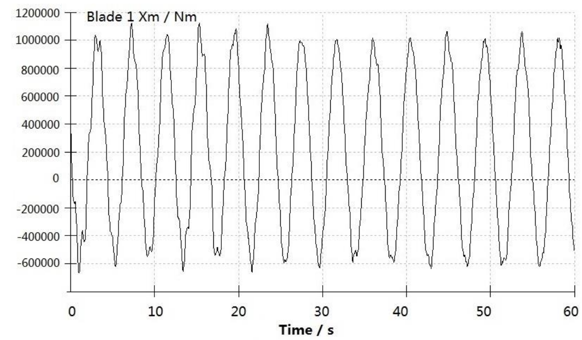

Fig. 4 Loads when wind speed is 9m/s

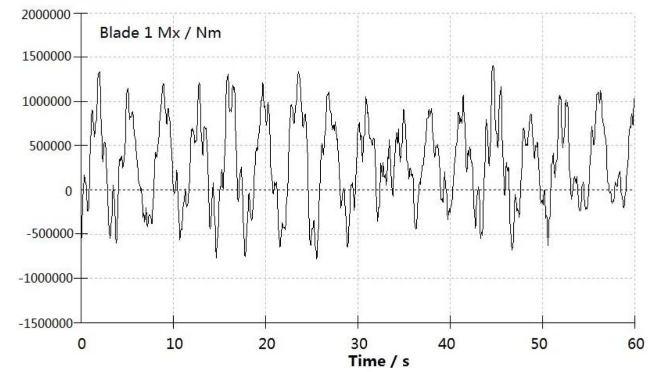

Fig. 5 Loads when wind speed is 25m/s

(2) Shut-down conditions (DLC3.1). The loads tend to a stable value during shutting down, no matter what wind condition is considered. But, the fluctuation under shut-down wind speed is small and is easy to converge to zero comparing to those of other two conditions.

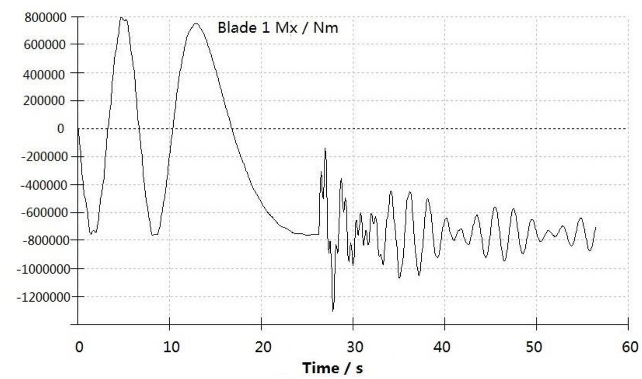

Fig. 6 Loads when wind speed is 3.5m/s

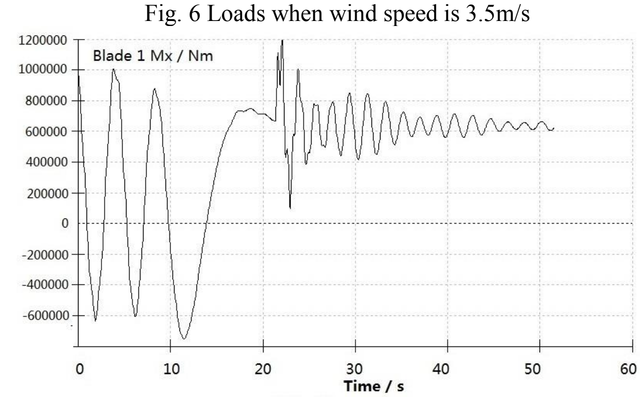

Fig. 7 Loads when wind speed is 9m/s

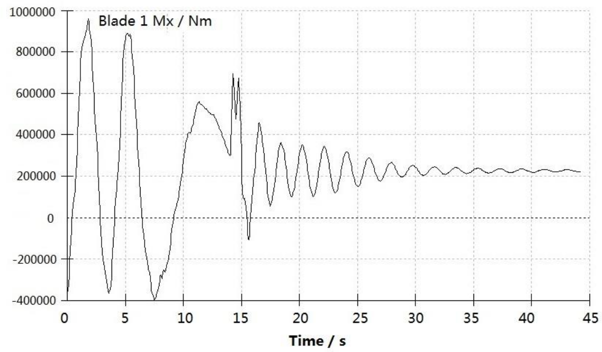

Fig. 8 Loads when wind speed is 25m/s

(3) Start-up conditions (DLC4.1). The amplitudes and fluctuation range of the loads are small and easily converge to a stable level, when WTs start up under cut-in wind speed. While under other wind conditions, the loads are large and fluctuate dramatically during starting up.

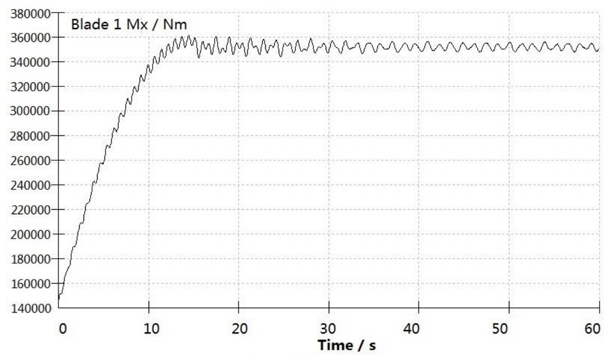

Fig. 9 Loads when wind speed is 3.5m/s

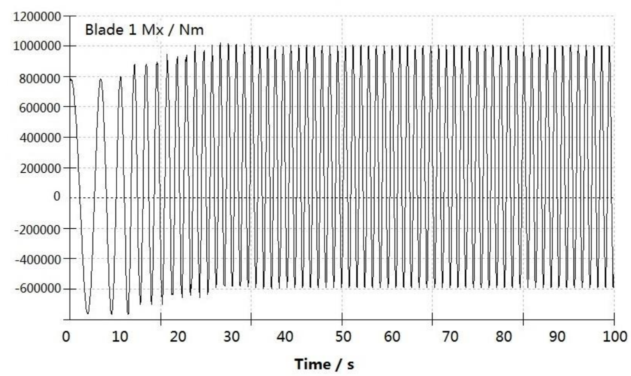

Fig. 10 Loads when wind speed is 9m/s

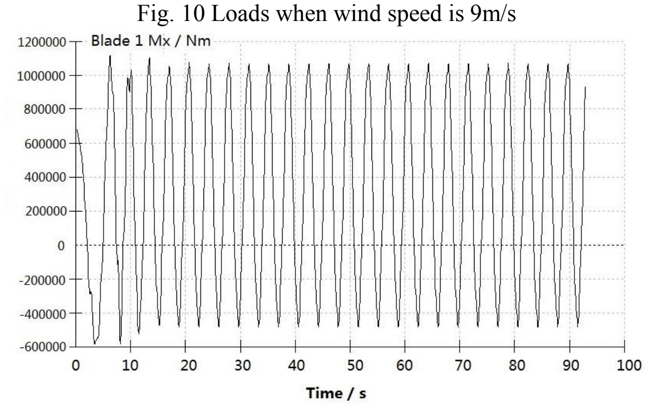

Fig. 11 Loads when wind speed is 25m/s

(4) Idling conditions (DLC6.4). The loads fluctuate at a small level and increase with the growth of wind speed.

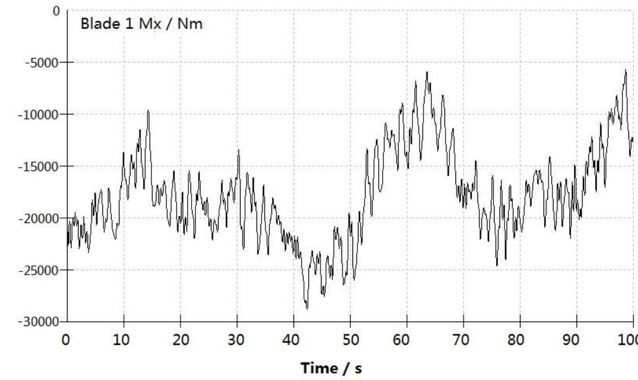

Fig. 12 Loads when wind speed is 3.5m/s

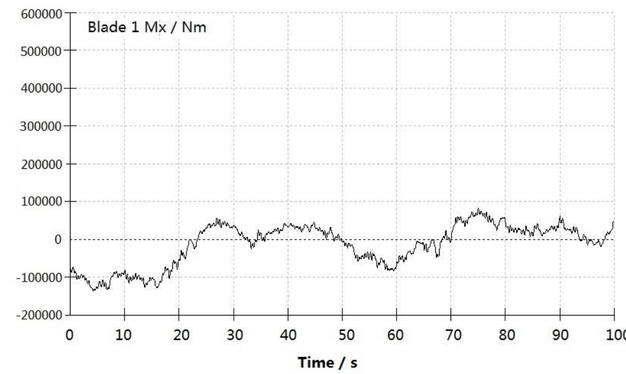

Fig. 13 Loads when wind speed is 9m/s

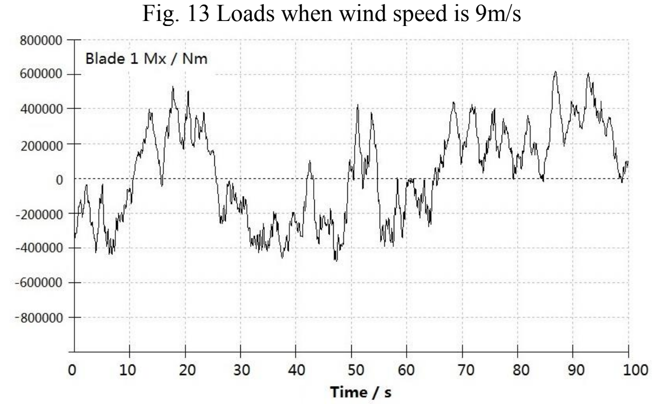

Fig. 14 Loads when wind speed is 25m/s

The proposed fatigue damage values (FDV) and lifetime equivalent fatigue loads (LEFL) at blade root [22] under various wind speed and working conditions are calculated and listed in Table I. It can be seen that blades suffer large and varying loads in different external conditions, which limits the total cycle counts. It is also clear that although with the same wind speed, loads are different under various working conditions. Therefore, it is significant to schedule WTs considering fatigue damage in a wind farm and to quantify this damage values considering both working condition and variable wind speed.

TABLE I
LIFETIME EQUIVALENT FATIGUE LOADS AND FATIGUE DAMAGE VALUE AT BLADE ROOT

Working Conditions	Wind Speed (m/s)	LEFL(kN•m)	Cumulative Cycle Counts	Relative FDV (min)
Generating	4	1948.9	2.42E+08	3.80E-08
	6	1967.4	2.33E+08	4.32E-08
	8	2016.1	2.12E+08	6.02E-08

	10	2050.7	1.98E+08	8.03E-08
	12	2020.1	2.10E+08	9.51E-08
	14	2000.2	2.18E+08	1.29E-07
	16	1964.2	2.35E+08	1.53E-07
	18	1942.8	2.45E+08	1.75E-07
	20	1947.6	2.43E+08	2.46E-07
	22	1964.9	2.35E+08	2.98E-07
	25	2004.5	2.17E+08	4.17E-07
Starting-up	4	956.2	4.18E+09	2.63E-09
	12	730.3	1.23E+10	1.22E-09
	25	674.5	1.69E+10	1.18E-09
Shutting-down	4	760.1	1.05E+10	2.77E-09
	12	634.6	2.15E+10	1.35E-09
	25	590.5	2.88E+10	1.15E-09
Idling	3	11.3	2.10E+17	5.25E-16

B. *Unit Commitment Results*

The interval forecasting data used in this paper are generated from RVM model and are drawn in Fig.15-16. With forecasting and its uncertainties, the objective function and constraint functions can be established. To validate the reliability of the proposed UC model, the optimization process is conducted repeatedly for five times.

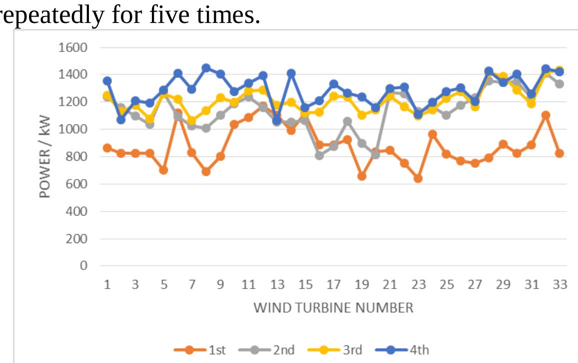

Fig.15 Wind power deterministic forecasting curves for each WT

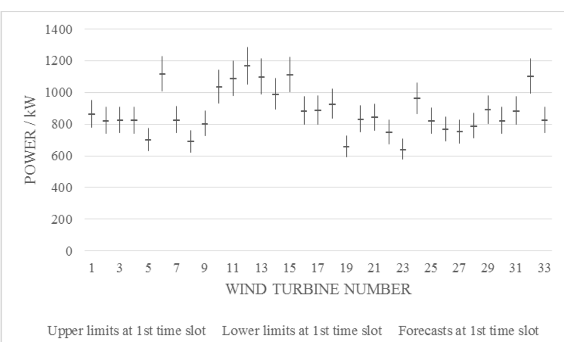

Fig.16 Wind power interval forecasting for each WT at 1st time slot

Table II-IV show the results in the 5-time simulations, in terms of optimal solutions (minimum fatigue damage value), converging iteration step numbers and computational times. It is observed that the obtained optimal solutions from GMA are better than solutions obtained by the other leading methods – PSO and GA. The proposed GMA approach has less fatigue damage than that of PSO and GA by 3.7% and 8.2%. Also, GMA outperforms GA and PSO in terms of reliability, convergence rate and computational efficiency. Specifically, GMA has 85.2% and 8.5% less iteration steps to converge; 44.5% and 13.0% higher computational efficiency. Besides, UC model considering WPF uncertainty has better performance (lower fatigue value) than UC without uncertainty estimation, no matter which optimization algorithm is used. GMA, PSO and GA reduce the mechanical losses by 15.9%, 11.8% and 7.1% on average comparing to UC without uncertainty consideration.

It validates the well representation and contribution of WPF uncertainty in UC problem.

TABLE II

OPTIMAL SOLUTIONS FOR GMA, PSO AND GA SEARCHING

NUMBER	GMA	PSO	GA	Without uncertainty
1st	2.816	2.974	3.014	3.386
2nd	2.840	2.863	3.096	3.269
3rd	2.790	2.951	3.050	3.592
4th	2.823	2.906	3.107	3.074
5th	2.832	2.928	2.990	3.025
Average	2.820	2.924	3.051	3.269

TABLE III

ITERATION NUMBERS FOR GMA, PSO AND GA SEARCHING

NUMBER	GMA	PSO	GA
1st	113	125	298
2nd	62	87	276
3rd	252	259	285
4th	175	193	294
5th	178	182	295
Average	156	169	289

TABLE IV

COMPUTATIONAL TIMES FOR GMA, PSO AND GA SEARCHING

NUMBER	GMA (s)	PSO(s)	GA (s)
1st	213	270	286
2nd	205	238	294
3rd	198	216	301
4th	205	219	289
5th	192	204	293
Average	203	229	293

The standard deviation of optimal solutions is 1.9% for GMA, while 4.3% for PSO and 5.1% for GA. It indicates that GMA is capable of searching global optimizations in a steadier and more reliable manner. Fig.17 is the GMA converging processes in five times simulations. The optimal solution in five times iterations varies, and sometimes the results might fall into local optimum at first, but finally converge to a global optimal solution. In general, the proposed GMA algorithm converges stably and efficiently.

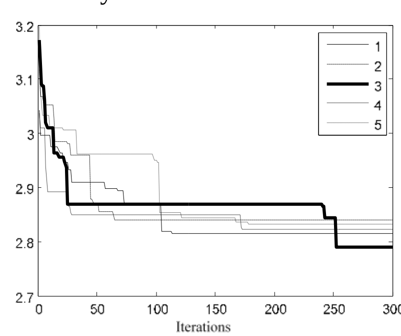

Fig. 17 Results of evolutionary process with GMA in 5 tests

The wind turbine scheduling results during four consecutive scheduling time point are drawn in Fig.18, where 0 and 1 indicate the shut-down and start-up state, respectively. Considering the demand requirements and minimizing damage losses, NO.5, NO.6, NO.7, NO.12, NO.16, and NO.18 wind turbines are in the shutdown status within this scheduling period. Based on the forecasting results with different forecast time horizon, different unit commitment optimization in future periods can be obtained, for example, day ahead scheduling or real time dispatching. The computational times shown in Table IV validate the GMA efficiency in a real time operation environment. Compared with traditional UC strategies in a wind farm, the proposed UC diminishes the random switches of WT on/off and the corresponding fatigue damages during operation.

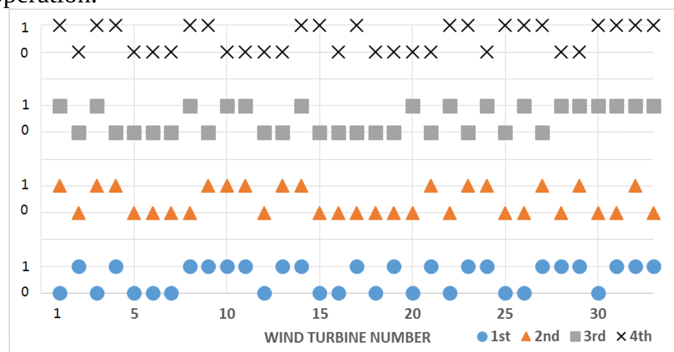

Fig.18 UC processing results of the wind farm

VI. Conclusions

In this paper, a wind farm unit commitment mathematical model is proposed based on qualifying the fatigue damage value of blades under various operational conditions and wind power forecasting uncertainty. A novel glowworm metaphor algorithm is implemented for solving the proposed unit commitment problem. The proposed UC is with the aim of minimizing the overall mechanical fatigue damages of wind turbine blades. The wind power forecasting uncertainty is quantified as the uncertain interval with given confidence level based on RVM theory and incorporated into UC constraints.

Compared with the traditional wind farm unit commitment, the proposed method reduces mechanical damage in a wind farm while satisfying constrains of wind power forecasting uncertainty and power system demand. It also has better reliability and higher computational efficiency in UC than that of PSO and GA. To sum up, this UC method reduces the number of on/off times, extends wind turbine lifespan, and mitigates forecasting uncertainty.

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