

SCUC Considering Loads and Wind Power Forecasting Uncertainties using Binary Gray Wolf Optimization Method

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Received: December 2017

Revised: April 2018

Accepted: July 2018

ABSTRACT:

Recently, the renewable resources such as wind farms assumed more attraction due to their features of being clean, no dependency to any type of fuel and having a low marginal cost. The output power of wind units is dependent on the wind speed which has a volatile and intermittent nature. This fact confronts the solution of unit commitment problem with some challenges when a huge amount of wind resources is penetrated and considerable uncertainties are included in the problem. Moreover, the demand of the system has some volatility in comparison with forecasted values. This kind of volatility and stochastic nature is another source of uncertainty in the power system. In this paper, thermal and wind units are incorporated and the optimization problem is solved by the employment of proper probability distribution function and the Monte Carlo simulation approach for dealing with uncertainties. Afterwards, the optimization problem is solved by the use of the binary form of gray wolf optimization algorithm and the minimized total cost will be obtained. Ultimately, the unit commitment schedule and optimal generation of each unit are determined and the optimization results are compared with the solution of genetic algorithm and particle swarm algorithm.

KEYWORDS: Security-Constrained Unit Commitment; Wind Power Plant; Gray Wolf Optimization Algorithm; Uncertainty; Monte-Carlo.

1. INTRODUCTION

In recent years, the tendency to exploit wind energy, as a renewable, cheap and large-scale energy source, is expanding rapidly. However, the increasing penetration of the wind units in the power systems, as well as the fluctuating and intermittent nature of their output power has encountered the secure and economic operation of power networks with various difficulties [1-2].

One of the main issues in power system operation is the unit commitment problem (UC) which determines the operation cost of the power system. The unit commitment problem is an important optimization tool to determine the ON/OFF state of units in the power system operation. The goal is to minimize the total costs of the system operation during the schedule period so that the system power equality between

generation and demand as well as other operational constraints must be satisfied. The unit commitment is usually a large-scale and mixed-integer nonlinear problem. Various methods, including heuristic methods [3], dynamic programming [4], genetic algorithm [5], particle swarm optimization algorithm [6], neural networks, mixed-integer linear programming [7], and Lagrangian relaxation method [8] have been employed to solve unit commitment problem. The high speed and accuracy of optimization algorithms, especially in large-scale problems such as unit commitment have caused widespread acceptance and prevalent employment for these algorithms [9]. A new optimization algorithm which is called gray wolf optimization (GWO) algorithm is recently proposed which has a brilliant performance for optimizing non-convex and non-smooth problems. It is inspired by the

social behavior of wolves while hunting [10]. The reference [11] has shown the performance of gray wolf optimization algorithm for an economic dispatch problem. The presences of distributed generation sources such as wind turbines in addition to the stochastic nature of wind energy incorporate uncertainty into the unit commitment problem. The measure of ignoring the uncertainty of such sources, considering them as a probabilistic and stochastic phenomenon, and modeling them by numerical and iterative methods are of suggested solutions to solve UC problem [12].

In this paper, the aforementioned algorithm is improved and readjusted to deal with the binary form which declares the novelty and uniqueness of this study. The contribution of this work is to solve the unit commitment problem employing GWO. Moreover, the unit commitment problem is solved by considering the presence of the wind and thermal power plants. Hence, the available uncertainties of wind power generation and forecasted loads are modeled in the problem by using the probability distribution function employing the Monte Carlo method. This method generates different scenarios for modeling the probable possibilities.

In the following parts, first of all, the unit commitment problem and its relevant constraints are explained. Then a brief description of the gray wolf optimization algorithm is addressed and it is expressed how to apply it in solving the problem. In addition, the Monte Carlo method is described, and different scenarios for consideration of uncertainty are defined. Finally, in order to find the lowest generation cost, the problem is solved in two cases of regard to or regardless of the system's security constraints. The results are also compared with simulation results of genetic and particle swarm optimization algorithms.

2. UNIT COMMITMENT PROBLEM WITH SECURITY CONSTRAINTS

2.1. Generation Costs

The generation costs of a thermal unit comprise the consumed fuel cost, the start-up cost of the unit, and the maintenance cost. Other costs such as shutdown cost of the unit are negligible. The fuel cost of thermal unit i at the time t , is shown by F_i in Eq. (1). It can be considered as a quadratic function of the unit's active output power that is defined by P_i as below:

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \quad (1)$$

Where, a_i , b_i and c_i are cost coefficients of the i_{th} generator [13].

If a unit is turned off, it should necessarily remain off for a specific time that is called minimum downtime

and is shown with MDT . After MDT , if the unit changes its state to ON state, the start-up process will be done by less cost because the boiler is somewhat warm yet. However, if the time of being in OFF state exceeds a certain amount of time (that is denoted by CST), it requires more start-up cost because the water temperature in the boiler is drastically decreased. The start-up cost of the i_{th} unit is shown by SUC which has two subcategories of hot start-up cost (HSC) and cold start-up cost (CSC), and $T_{off,i}$ stands for the time when the unit has been in OFF state after the elapsed time of MDT . The start-up cost can be described by Eq. (2):

$$SUC_i = \begin{cases} HSC_i & , \text{ if } MDT_i(t) \leq T_{off,i} \leq MDT_i(t) + CST_i \\ CSC_i & , \text{ if } T_{off,i} > MDT_i(t) + CST_i \end{cases} \quad (2)$$

The maintenance cost can also be obtained from Eq. (3) [14].

$$MC_i(P_i) = d_i + f_i P_i \quad (3)$$

Where MC is the maintenance cost of the i_{th} thermal unit, P is the generated power of i_{th} thermal unit; d and f are constant numbers which are dedicated to each unit according to their technical characteristics. Therefore, the total cost of the generation, the objective function of the unit commitment problem, is proposed in Eq. (4) and must be minimized [15].

$$TC = \sum_{i=1}^N \sum_{t=1}^H [F_i(P_i) + MC_i(P_i) + SUC_i(1 - I_i(t-1))] \times I_i(t) \quad (4)$$

Where TC is the total cost of the thermal units' generation, N represents the number of thermal units; H is the time domain that is 24 hours in this article. The variable of I shows the ON and OFF state of the i_{th} unit. If the unit is ON, the value of I is 1, otherwise, it is 0.

2.2. Unit Commitment Constraints

The generated power by all ON units must meet the required load as well as the system losses. The power balance constraint of the system for hour t hour is according to Eq. (5) [16].

$$\sum_{i=1}^N I_i(t) \times P_i(t) + \sum_{j=1}^{N_w} P_{w,j}(t) = P_D(t) + P_{Loss}(t) \quad (5)$$

Where P and N are the generated power and the number of thermal units respectively, P_w and N_w are the wind units' power production and the number of wind units respectively, P_{Loss} indicates the network losses, and P_D is the demand of the system.

On the other hand, to have sufficient reliability in the network, sufficient spinning reserve resources must be provided in the network. The presence of wind units and their correlated uncertainty increase the network

reserve requirements to some extent. According to Eq. (6), the required spinning reserve amount is equal to 5% of the network demand plus by 10% of the total wind power generation [17].

$$\sum_{i=1}^N I_i(t) \times P_i^{\max}(t) + \sum_{j=1}^{N_w} P_{w,j}(t) = (1.05 \times P_D(t)) + P_{Loss}(t) + \left(0.1 \times \sum_{j=1}^{N_w} P_{w,j}(t) \right) \quad (6)$$

However, according to Eq. (7), the i_{th} thermal unit has a definite range for power generation [18].

$$I_i(t) \times P_i^{\min}(t) \leq P_i(t) \leq I_i(t) \times P_i^{\max}(t) \quad (7)$$

Another operational constraint of the unit commitment problem is the minimum up/down time constraint which means the least time of remaining ON/OFF after the unit is turned ON/OFF. When a unit is ON/OFF, there is a minimum pre-specified time after which the unit can again change its state to OFF/ON. Thus, the minimum uptime and minimum downtime are shown by MUT and MDT respectively that can be obtained by Eq. (8) and Eq. (9).

$$\left\{ \begin{array}{l} \sum_{t=1}^{L_i} [1 - I_i(t)] = 0 \\ \sum_{t=L_i+1}^{t+MUT_i-1} I_i(t) \geq MUT_i \times Y_i(t), \quad \forall t = L_i + 1 \dots T - MUT_i + 1 \\ \sum_{t=T-MUT_i+2}^T [I_i(t) - Y_i(t)] \geq 0, \quad \forall t = T - MUT_i + 2 \dots T \\ L_i = \text{Min}\{T, (MUT_i - U_i^0) \times I_i(0)\} \end{array} \right. \quad (8)$$

$$\left\{ \begin{array}{l} \sum_{t=1}^{B_i} I_i(t) = 0 \\ \sum_{t=1}^{t+MDT_i-1} [1 - I_i(t)] \geq MDT_i \times Z_i(t), \quad \forall t = B_i + 1 \dots T - MDT_i + 1 \\ \sum_{t=T-MDT_i+2}^T [1 - I_i(t) - Z_i(t)] \geq 0, \quad \forall t = T - MDT_i + 2 \dots T \\ B_i = \text{Min}\{T, (MDT_i - S_i^0) \times (1 - I_i(0))\} \end{array} \right. \quad (9)$$

Where U_i^0 is the duration of being ON until hour 0, $Y_i(t)$ is the start-up indicator of i_{th} unit at hour t , L_i is the duration that the unit must stay ON at the beginning of the period, S_i^0 is the duration of being OFF before hour 0, $Z_i(t)$ is the shutdown indicator of the i_{th} unit at hour t , and B_i is the duration that the unit must stay OFF at the beginning of the period [19].

Moreover, the solution of the unit commitment problem is simplified by assuming that all the generation and consumption centers of the network are connected to a common bus. This assumption results in ignoring the limits of load flow in the power network. These limitations include bus voltage restrictions,

active and reactive power flow in transmission lines, the grid frequency, and the buses' phase difference, which all must be in the permitted range. In this paper, load flow results are provided at each algorithm's iteration so that the bus voltage constraints and transmission lines' limits must be in the permitted range. The mentioned limitations are considered as the network security constraints while solving the problem. For stable operation of the system, each bus voltage (V_b) needs to be within the specified range (for example 1.05 p.u. to 0.95 p.u.) permanently [20].

$$V_B^{\min}(t) \leq V_B(t) \leq V_B^{\max}(t) \quad (10)$$

Also, the transmitting power of a line must always be within a specified range (between the maximum and minimum tolerable transmission power of line).

$$P_{Line(i,j)}^{\min}(t) \leq P_{Line(i,j)}(t) \leq P_{Line(i,j)}^{\max}(t) \quad (11)$$

3. THE OPTIMIZATION ALGORITHM

3.1. Gray Wolf Optimization Algorithm

The Gray wolf optimizer algorithm is one of the novel evolutionary algorithms which is inspired by the hierarchical structure of leadership and social behavior of wolves on the hunt, and it is suggested by Mir-Jalili, et.al, in 2014 [21]. Gray wolves often prefer to live in a group which is called pack and the number of pack's members is usually between 5 to 12 wolves on average. They have strict rules in the social hierarchy. According to [21], gray wolves' packs consist of four types:

1. Alpha wolves (α) who are the leaders of the pack. The alpha wolves are responsible for making decisions which must be performed in the pack.

2. Beta wolves (β) include those who help Alpha in decision-making and other activities. Betas can be male or female; they are the best candidates for becoming the alpha.

3. Omega wolves (ω) play the role of victim. They should always obey other wolves and they are the last that are allowed for eating.

4. Delta wolves (δ or subordinate) should obey Beta and Alpha wolves. But they have domination over the omega wolves. Scouts, Sentinels, Elders, Hunters, and Caretakers belong to this category. Scouts are responsible for inspecting boundaries of the territory and warning the pack in dangerous situations. Sentinels guarantee the pack security and protect the pack. Elders are the experienced wolves who used to be beta and alpha type before. Hunters help beta and alpha wolves while hunting the prey and maintaining food for the pack. The Caretakers are responsible caring of wounded, sick or weak wolves in the pack. Fig. 1 illustrates the position updating in GWO algorithm.

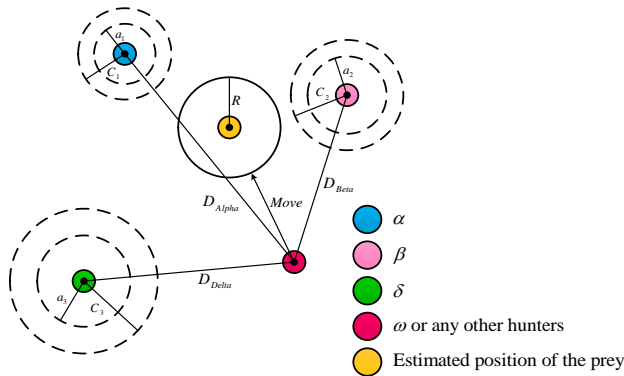


Fig.1. Position updating in GWO [21].

In the GWO mathematical model of the hierarchy of wolves' pack, the optimal solution is the α type. The second and third fittest solutions are β and δ respectively. Other solutions are assumed to be a candidate for ω . The GWO algorithm uses α , β and δ solutions to change the direction of the prey (guiding of hunting) and ω wolves follow these three solutions.

In order to hunt, the pack of wolves encircle the prey. In order to simulate the prey encircling behavior, Eq. (12) to (15) are used.

$$\bar{X}(t+1) = \bar{X}_p(t) + \bar{A} \cdot \bar{D} \quad (12)$$

Where t is the number of iteration, \bar{A} and \bar{C} are coefficients vectors, \bar{X}_p represents the prey position, and \bar{X} is the gray wolf position. The value of \bar{D} is defined by Eq. (13):

$$\bar{D} = |\bar{C} \cdot \bar{X}_p(t) - \bar{X}(t)| \quad (13)$$

The values of \bar{A} and \bar{C} can also be calculated by Eq. (14) and (15).

$$\bar{A} = 2a \cdot \bar{r}_1 - a \quad (14)$$

$$\bar{C} = 2\bar{r}_2 \quad (15)$$

In the above equation, a is a linearly decreasing variable over the course of iterations from 2 to 0. r_1 and r_2 are random vectors within the interval of [0, 1]. The hunt is often guided by the Alpha wolves. The beta and delta wolves may occasionally participate in the hunt.

In order to conduct the mathematical modeling of the gray wolf hunt behavior, the α (the best candidate solution), β (the second-best candidate solution) and δ (the third best candidate solution) are used assuming that they have the best knowledge about the position of their prey respectively. Therefore, the three best solutions are determined and the other searching factors such as the omega are forced to update their position

according to the best searching factors' position. The Eq. (16) is used to update the position of wolves.

$$\bar{X}(t+1) = (\bar{X}_1 + \bar{X}_2 + \bar{X}_3)/3 \quad (16)$$

Where \bar{X}_1 , \bar{X}_2 , and \bar{X}_3 are defined in Eq. (17) to (19).

$$\bar{X}_1 = |\bar{X}_\alpha - \bar{A}_1 \cdot \bar{D}_\alpha| \quad (17)$$

$$\bar{X}_2 = |\bar{X}_\beta - \bar{A}_2 \cdot \bar{D}_\beta| \quad (18)$$

$$\bar{X}_3 = |\bar{X}_\delta - \bar{A}_3 \cdot \bar{D}_\delta| \quad (19)$$

Where \bar{X}_α are the positions of the \bar{X}_δ and \bar{X}_β first three best solutions that are obtained at iteration t . \bar{A}_1 , \bar{A}_2 , and \bar{A}_3 can be calculated by Eq. (14). In addition, \bar{D}_α , \bar{D}_β , and \bar{D}_δ are presented in Eq. (20) to (22).

$$\bar{D}_\alpha = |\bar{C}_1 \cdot \bar{X}_\alpha - \bar{X}| \quad (20)$$

$$\bar{D}_\beta = |\bar{C}_2 \cdot \bar{X}_\beta - \bar{X}| \quad (21)$$

$$\bar{D}_\delta = |\bar{C}_3 \cdot \bar{X}_\delta - \bar{X}| \quad (22)$$

Where \bar{C}_1 , \bar{C}_2 and \bar{C}_3 are defined in Eq. (15).

The final condition about the GWO is the parameter a that is used in Eq. (14). This condition is employed to control the trade-off between exploration (searching for a prey) and exploitation (attacking to a prey). The parameter a will be updated in each iteration in a linear manner from 2 to 0 according to the Eq. (23) [22].

$$a = 2 - t \frac{2}{MaxIter} \quad (23)$$

Where t is the number of iterations and $MaxIter$ is the total number of iterations for optimization. Finally, the gray wolf optimization algorithm is described as follows:

<p>input: n Number of gray wolves in the pack, N_{Iter} Number of iterations for optimization.</p> <p>output: x_α Optimal gray wolf position, $f(x_\alpha)$ Best fitness value</p> <ol style="list-style-type: none"> 1. Initialize a population of n gray wolves' positions randomly. 2. Find the α, β and δ solutions based on their fitness values. 3. while Stopping criteria not met do <ul style="list-style-type: none"> foreach wolf: ϵ pack do <ul style="list-style-type: none"> Update current wolf's position according to Eq (16). end <ul style="list-style-type: none"> I Update a, A and C II Evaluate the positions of individual wolves. III Update α, β and δ end 4. Return α

Fig. 2. The gray wolf optimization algorithm [23].

3.2. Binary Gray Wolf Optimization (BGWO) Algorithm

In the gray wolf optimization, the wolves change their positions continuously at any point in the search space. In some specific problems such as feature selection, the solutions are limited to binary values within [0, 1] which have promoted a developed version of GWO. In the binary gray wolf optimization (BGWO), the update equation of wolves is a function of the three position vectors. It means, X_α , X_β and X_δ describe the positions of each wolf regard to the three best solutions and can determine the attraction rate of each wolf. In the BGWO, the solutions are shown in the binary form at any time. All solutions are in the corner of the three-dimensional cube [23].

In the BGWO method, the original equation can be updated according to Eq. (24).

$$X_i^{t+1} = \text{Crossover}(x_1, x_2, x_3) \quad (24)$$

Where $\text{Crossover}(x, y, z)$ is a suitable cut between x, y, z solutions and x_1, x_2, x_3 which show the binary vectors of wolf motion effect toward the alpha, beta and delta wolves respectively. x_1, x_2, x_3 are calculated using Eq. (25).

$$x_j^d = \begin{cases} 1 & \text{if } (x_i^d + bstep_i^d) \geq 1 \\ 0 & \text{otherwise} \end{cases}, i \in \{\alpha, \beta, \delta\}, j \in \{1, 2, 3\} \quad (25)$$

Where x_i^d is the position vector of each of alpha, beta, and delta wolves in the dimension of d , and $bstep_i^d$ is a binary step of wolves in the dimension of d that is calculated by Eq. (26).

$$bstep_i^d = \begin{cases} 1 & \text{if } cstep_i^d \geq rand \\ 0 & \text{otherwise} \end{cases}, i \in \{\alpha, \beta, \delta\} \quad (26)$$

Where $rand$ is a random number generated from a uniform distribution within [0, 1], and $cstep_i^d$ is the constant effective step length in dimension d for each of alpha, beta, delta wolves and is calculated using the sigmoid function in Eq. (27).

$$cstep_i^d = \frac{1}{1 + e^{-10(A_i^d D_i^d - 0.5)}}, i \in \{\alpha, \beta, \delta\} \quad (27)$$

Where D_i^d and A_i^d are calculated using Eq. (20) to (22) and Eq. (14) at the dimension of d . A simple random cutting strategy in each dimension is the cutting solutions for a, b , and c that is shown in Eq. (28).

$$x_d = \begin{cases} a_d & rand < 1/3 \\ b_d & 1/3 \leq rand < 2/3 \\ c_d & otherwise \end{cases} \quad (28)$$

Where a_d, b_d, c_d are binary values for the first, second and third parameters in dimension d . x_d is the output of cutting in the dimension of d , and $rand$ is a random number taken from a uniform distribution from the interval [0, 1]. Finally, BGWO algorithm is described as follows:

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input: n Number of gray wolves in the pack, Niter Number of iterations for optimization.
output: xα Optimal gray wolf position, f(xα) Best fitness value.

1. Initialize a population of n gray wolves positions random ∈ [0,1]
2. Find the α, β and δ solutions based on their fitness values.
3. while Stopping criteria not met do
   foreach wolf i ∈ pack do
     if |A| < 1
       Calculate x1, x2, x3 using Eqs (17), (18), (19)
       xit+1 ← Crossover among x1, x2, x1-x3 using Eq. (24)
     else
       Calculate new x1, x2, x3
       xit+1 ← Crossover among x1, x2, x3 using Eq. (24)
     endif
   end
   I Update a, A and C
   II Evaluate the positions of individual wolves.
   III Update α, β and δ
 end
4. Return a

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Fig. 3. The BGWO algorithm [23].

4. MONTE CARLO METHOD

The presence of the wind power plant in the network, the stochastic behavior of the wind and load consumption have caused the uncertainty in the power generation models. This uncertainty has inclusion in solving the unit commitment problem with regard to the obligation of load and generation balance at any moment. The Monte Carlo approach is a probabilistic and statistic method in order to take the uncertainty into account [24]. In this method a large number of scenarios are generated, which is based on the imbalances of all uncertain variables. In another word, each scenario represents a possible occurrence for forecasted variables. When a large number of scenarios are defined, the combination of probabilities of scenarios will be led to the most optimistic, the most pessimistic, and the most possible scenarios. Scenario reduction approaches can also be employed to reduce the size of the problem, diminish the computational burden, and increase the solution speed.

4.1. Wind Plants Uncertainty

The scattering of the mean wind speed in different months of a year for the wind site, located in the city of Taft, Yazd, Iran, is shown in Fig. 4.

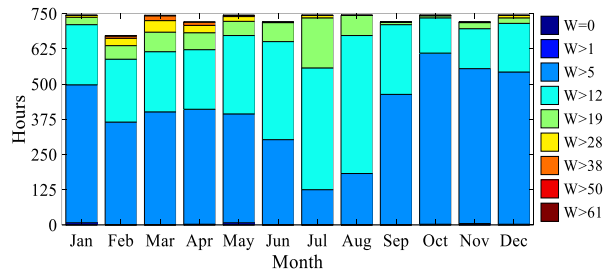


Fig. 4. Hourly average wind speed for a specific day.

The actual amounts of wind speed at each hour always have a difference with its average amount. The wind speed behavior can be approximated as a random variable with a normal distribution function. In the Monte Carlo method, the uncertainties can be modeled through various scenarios by employing the cumulative probability density curve (CDF). The output power of wind farm can be calculated by the Eq. (29).

$$P_{wt} = \begin{cases} 0 & 0 < v < v_{ci} \\ a \times v^3 - b \times P_r & v_{ci} < v < v_r \\ P_r & v_r < v < v_{co} \\ 0 & v_{co} < v \end{cases} \quad (29)$$

In the above equation, $b = v_{ci}^3 / (v_r^3 - v_{ci}^3)$ and $a = P_r / (v_r^3 - v_{ci}^3)$, P_r is the rated power of wind turbine, V_{ci} is the cut-in speed, V_r is the rated speed, and V_{co} is the cut-out speed. Moreover, to determine the speed in the reference height of h_r , the mean daily wind speed is used in the following model:

$$v = v_{hr} \times (h/h_r)^\gamma \quad (30)$$

Where v is the wind speed at the height of h , V_{hr} is the wind speed at the height of h_r , and γ is the permissible power which is a value between $1/7$ to $1/4$ [25-27]. The power curve of wind plant speed is shown in Fig. 5.

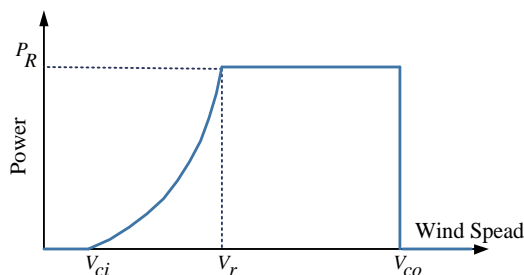


Fig. 5. Wind turbine generation curve.

In the Monte Carlo method, first of all, a random number must be generated with a uniform distribution function between 0 and 1. Now, by consideration of this random number which is assumed to be y in the CDF diagram, the corresponded x will be achieved through the diagram. The resulted number is the wind speed at that hour. Thus, the value of actual wind speed is obtained in this scenario; the wind farm generation in this scenario will be achieved based on the wind speed. Besides, thermal units' generation level, as well as the total cost of production in this scenario, will be determined. Assuming, for example, repeating 500 scenarios of this procedure for 500 times will result in 500 values for wind speed and therefore, 500 values for the wind power generation and a total cost of generation will be calculated for each scenario. Finally, because the probability of the entire 500 scenarios was the same, the total cost is equal to the average of these 500 costs. If the number of scenarios is N_s , the final cost that should be minimized is obtained from Eq. (31).

$$TC = \frac{1}{N_s} \sum_{s=1}^{N_{sc}} TC_s \quad (31)$$

The random behavior of network load consumption is modeled exactly in the same way by the Monte Carlo method in the unit commitment problem with respect to satisfying security margins [28].

4.2. The Uncertainty of Load Consumption

To consider the uncertainty of the load, the Monte Carlo method is employed. The normal distribution is selected to model the load [29].

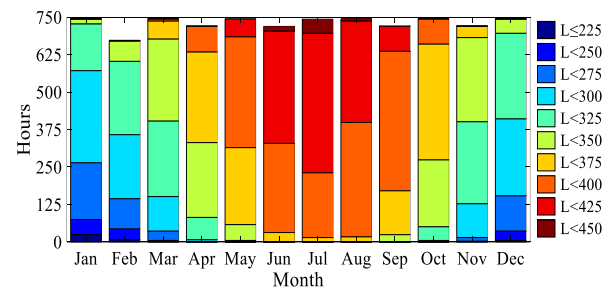


Fig. 6. The hourly changes of the load consumption during a day

The overall scattering diagram of loads of Taft city in one year is shown in Fig. 6. Its distribution function diagram for 12 p.m. o'clock is shown in Fig. 7.

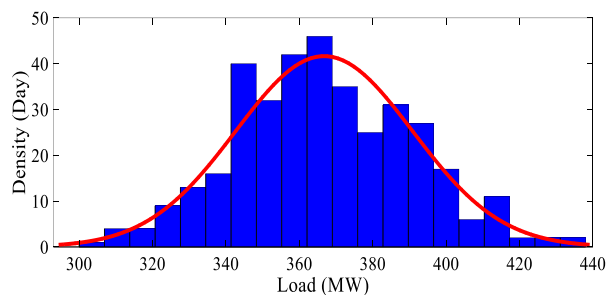


Fig. 7. The probability density function of the load consumption at 12 pm.

The flowchart of Fig. 8 illustrates the methodology of the problem including uncertainty modelling for forecasted variables.

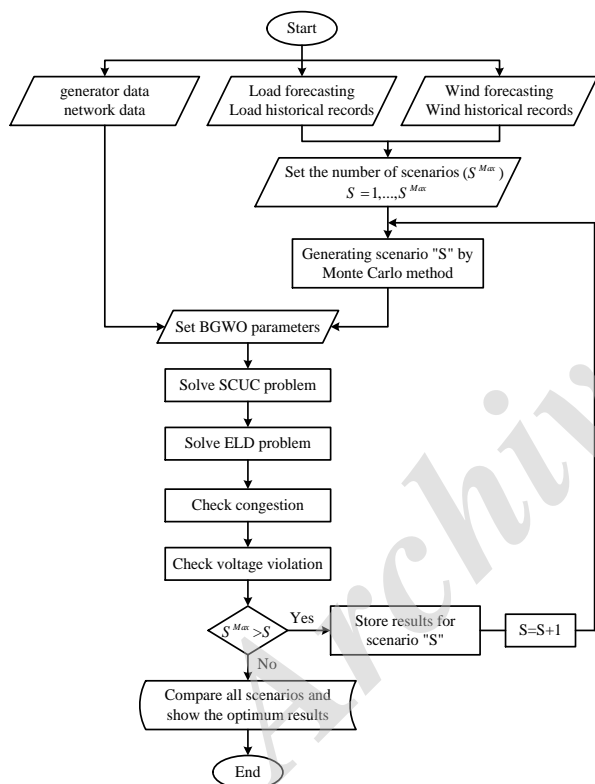


Fig. 8. The probability density function of the load consumption at 12 pm.

5. SIMULATION RESULTS

Our goal is to solve the unit commitment problem subject to meet the network’s security constraints in the presence of the distributed generators by considering the wind and load uncertainty. In this paper, the standard IEEE 30-bus test system that is shown in Fig. 9 is used to show the effectiveness of the proposed method. This system includes 9 thermal power plants and a wind farm, which are dispersed through 10 different buses of the network. The data of generators

and network parameters are adopted from [30-31]. The wind farm generation curve and the average load consumption are both depicted in Fig. 10.

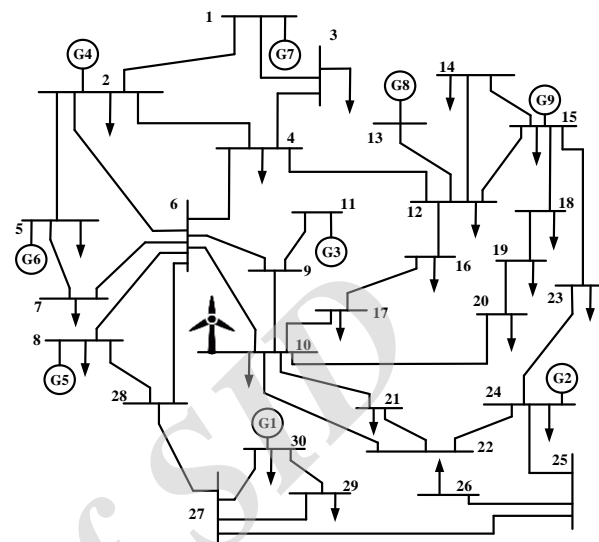


Fig. 9. The single-line diagram of the IEEE 30-bus system in the presence of a wind farm.

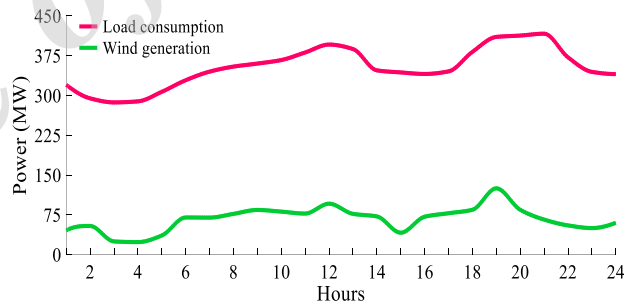


Fig. 10. The wind farm generation curve and the average load consumption.

This problem is solved in two different cases. Once, it is solved without consideration of the network security constraints, and then it is evaluated by taking these constraints into consideration. The Monte Carlo method is applied in order to model the uncertainty, and the gray wolf optimization algorithm is employed to optimize the problem. Two binary variables are imposed to represent the ON/OFF state of the corresponding thermal unit at each hour. The overall results are described in a matrix consists of 9 rows representing the 9 thermal units and 24 columns representing the 24 hours of a day. Due to inclusion of binary variables in the problem, the binary form of the gray wolf optimization algorithm is employed to minimize the total cost of generation. In order to specify the ON/OFF state of thermal units at each hour, in the BGWO algorithm, the matrix of optimum states for each member of the population should be

determined. Consequently, inside the sub-problem loop, the economic load dispatch is computed to dedicate a specific amount of generation for the units, which are deserved to be ON. When the optimized power generation of thermal units at each hour is determined, the Newton-Raphson load flow method will be applied to evaluate the load flow analysis and to check bus voltage limitations and lines' flow condition. The total cost of generation is also calculated based on the thermal units' power generation for each member of the population at all iterations. In the first scenario, by the employment of MATLAB 2017a software, regardless of the network security constraints, the algorithm has reached the optimum amount of the generation cost of \$124057.1365. Fig. 11 shows the unit commitment results and power dispatch within thermal units. The total average (within all hours) of the mean hourly electricity prices (within all units) is \$17.3667 in this scenario. Besides, the total start-up and shut down cost is about \$575 in scenario 1. The load flow analysis of this scenario expresses that if the optimum power schedule is implemented for the 30-bus network, the voltage of 35 buses within entire period of study, and the power flow of the lines 1-2 and 1-3 (in 24 hours), line 2-6 (in 6 hours), and line 3-4 (in 17 hours) exceed the permitted limit. Therefore, this optimal solution does not meet the security of the system.

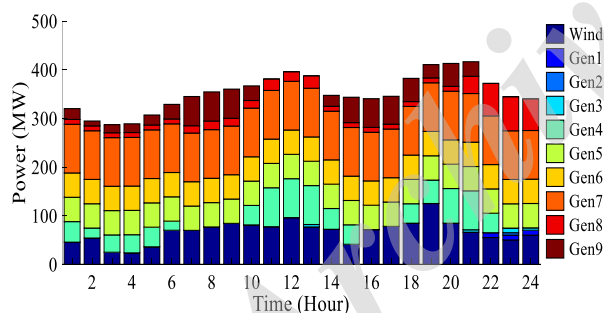


Fig. 11. The unit commitment and power dispatch in the IEEE 30-bus test system (scenario 1).

In the second scenario, in all iterations, the unit commitment and economic dispatch of the 30-bus network are calculated so that the relevant load flow results are kept in its allowable ranges, and the bus voltages and the transmission line limits do not violate the permitted range or tolerable power restrictions. The BGWO algorithm has achieved the lowest generation cost of \$129479.5981, which shows an increased rate of 4.37%. The total average (within all hours) of the mean hourly electricity prices (within all units) is enhanced up to \$18.12576 in the second scenario. In addition, the accumulated start-up and shut down cost has increased to \$757.934. Fig. 12 shows the unit commitment and the power dispatch between thermal

units at each hour. As it is obvious, the contribution of some units in term of amount of generation is changed, which is due to the imposition of transmission and voltage limits. In another word, the generation must be materialized in less congested areas.

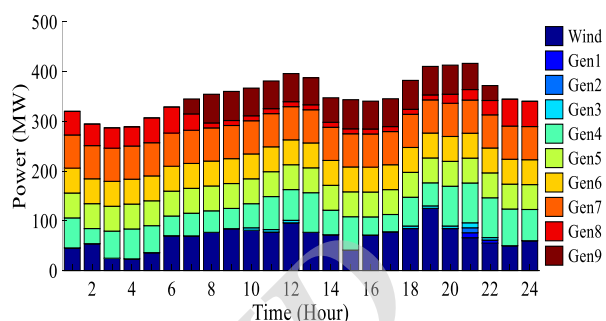


Fig. 12. The unit commitment and power dispatch in the IEEE 30-bus test system (scenario 2).

Figs. 13 and 14 demonstrate the hourly total costs and hourly average costs of the operation, respectively. As it shown, the second scenario has almost always higher prices and costs than the first scenario.

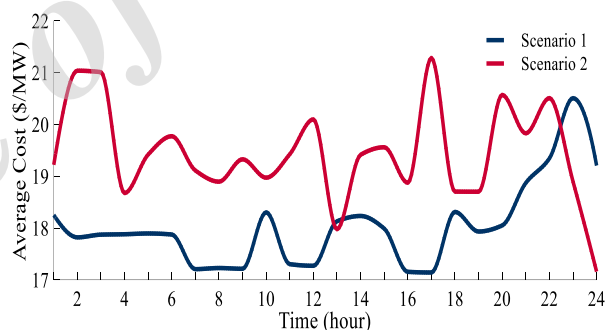


Fig. 13. The hourly average costs of scenarios.

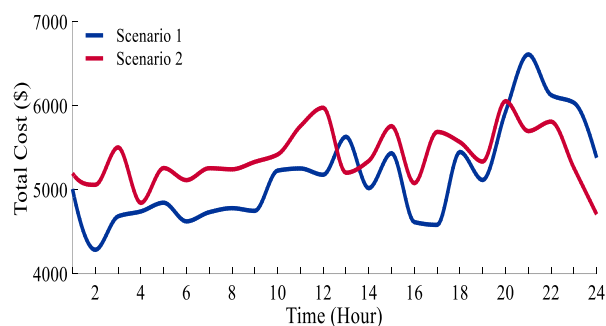


Fig. 14. The hourly total costs of the operation in both scenarios.

To evaluate the performance of the BGWO algorithm for determining the optimal response, the above problem is also solved again with two very applicable algorithms of genetic and particle swarm optimization and the results are compared with each

other. Fig. 15 shows the obtained total optimal cost in different iterations of the three algorithms for solving the security constraints unit commitment which are illustrated by red, blue and green colors respectively.

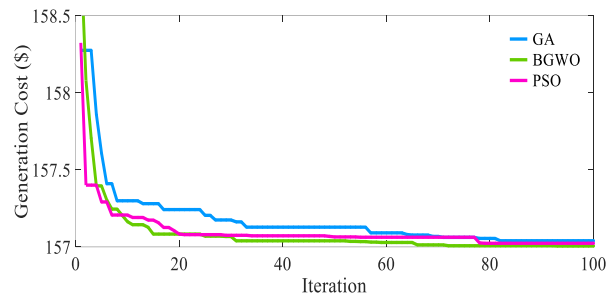


Fig. 15. The comparison of the lowest generation cost by GA, PSO and BGWO.

As this figure shows, in terms of convergence to the optimal solution, the BGWO algorithm has performed much better than the two other algorithms. The optimal cost of the gray wolf optimization algorithm is lower than GA and PSO algorithms. The reason is that the BGWO has a more extensive searching space which is resulted from the dynamic search path-finding of BGWO as the improved form of some algorithms such as genetic. Finally, it should be noted that solving the unit commitment problem with considering security constraints in the presence of wind units that contain considerable uncertainty must be modeled by probabilistic scenario-based approaches such as the Monte Carlo method which requires lots of computations and spending lots of time. Therefore, employing some algorithms such as the BGWO, which have higher convergence rate can be essential and helpful.

6. CONCLUSION

The integration of the intermittent wind energy in a unit commitment scheduling considering security constraints as well as the stochastic nature of the load consumption include various uncertainties in determining the optimal solution of the UC problem. The probabilistic and statistical approaches such as the Monte Carlo method can be employed to model the uncertainty. However, the employment of such approaches increases the simulation time due to increase in computation size. In this paper, the binary form of the gray wolf optimization algorithm, which has a better convergence than other optimization algorithms, is used. The optimal solution of the unit commitment problem is calculated with and without taking the security constraints into account. The results are compared with two conventional PSO and GA algorithms. The results show the better performance of the BGWO algorithm compared to two other algorithms.

REFERENCES

- [1] Sh. Chengcheng, X. Wang, M. Shahidehpour, X. Wang, and B. Wang. "Security-Constrained Unit Commitment with Flexible Uncertainty Set for Variable Wind Power." *IEEE Transactions on Sustainable Energy* 8, No. 3, pp. 1237-1246, 2017
- [2] R. Hemmati, H. Saboori, and S. Saboori. "Stochastic Risk-Averse Coordinated Scheduling of Grid Integrated Energy Storage Units in Transmission Constrained Wind-Thermal Systems Within a Conditional Value-At-Risk Framework." *Energy* 113, pp. 762-775, 2016.
- [3] F. Bavafa, T. Niknam, R. Azizipanah-Abarghooee, and V. Terzija. "A New Biobjective Probabilistic Risk-Based Wind-Thermal Unit Commitment using Heuristic Techniques." *IEEE Transactions on Industrial Informatics* 13, No. 1, pp. 115-124, 2017.
- [4] R., Aiying, P. B. Luh. "A Dynamic Regrouping Based Dynamic Programming Approach for Unit Commitment of the Transmission-constrained Multi-site Combined Heat and Power System." *IEEE Transactions on Power Systems*, 2017.
- [5] M. Nemat, M. Braun, and S. Tenbohlen. "Optimization of Unit Commitment And Economic Dispatch in Microgrids Based on Genetic Algorithm and Mixed Integer Linear Programming." *Applied Energy*, 2017.
- [6] A. Najafi, M. Farshad, and H. Falaghi. "A New Heuristic Method to Solve Unit Commitment by using a Time-Variant Acceleration Coefficients Particle Swarm Optimization Algorithm." *Turkish Journal of Electrical Engineering & Computer Sciences* 23, No. 2, pp. 354-369, 2015.
- [7] C., Bruno, J. Soares, P. Faria, and Z. Vale. "Mixed Integer Non-Linear Programming and Artificial Neural Network Based Approach to Ancillary Services Dispatch in Competitive Electricity Markets." *Applied energy* 108, pp. 261-270, 2013.
- [8] Y., Xiang, X. Zhang. "Unit Commitment using Lagrangian Relaxation and Particle Swarm Optimization." *International Journal of Electrical Power & Energy Systems* 61, pp. 510-522, 2014.
- [9] F. Barani, M. Mirhosseini, H. Nezamabadi-pour, and M. M. Farsangi. "Unit Commitment by an Improved Binary Quantum GSA." *Applied Soft Computing* 60, pp. 180-189, 2017.
- [10] S. A. Mirjalili, Sh. Saremi, S. M. Mirjalili, and Leandro dos S. Coelho. "Multi-Objective Grey Wolf Optimizer: A Novel Algorithm for Multi-Criterion Optimization." *Expert Systems with Applications* 47, pp. 106-119, 2016.
- [11] S. Mohd Herwan, Z. Mustafa, M. Ruslim Mohamed, and O. Aliman. "Using The Gray Wolf Optimizer for Solving Optimal Reactive Power Dispatch Problem." *Applied Soft Computing* 32, pp. 286-292, 2015.
- [12] Uçkun, Canan, Audun Botterud, and John R. Birge. "An Improved Stochastic Unit Commitment Formulation to Accommodate Wind Uncertainty." *IEEE Transactions on Power Systems* 31, No. 4, pp. 2507-2517, 2016.
- [13] H. Shahinzadeh, S. Hamid Fathi, M. Moazzami, and S.

- H. Hosseini. "Hybrid Big Bang-Big Crunch Algorithm for Solving Non-Convex Economic Load Dispatch Problems." In *Swarm Intelligence and Evolutionary Computation (CSIEC), 2017 2nd Conference on*, pp. 48-53. IEEE, 2017.
- [14] H. Shahinzadeh, M. Moazzami, D. Fadaei, and S. Rafiee-Rad. "Glowworm Swarm Optimization Algorithm for Solving Non-Smooth and Non-Convex Economic Load Dispatch Problems", In *Fuzzy and Intelligent Systems (CFIS), 2017 5th Iranian Joint Congress on*, pp. 103-109. IEEE, 2017.
- [15] R. Hemmati, H. Saboori. "Short-Term Bulk Energy Storage System Scheduling for Load Leveling in Unit Commitment: Modeling, Optimization, And Sensitivity Analysis", *Journal of advanced research* 7, No. 3, pp. 360-372, 2016.
- [16] H. Shahinzadeh, S. M. Nasr-Azadani, and N. Jannesari. "Applications of Particle Swarm Optimization Algorithm to Solving the Economic Load Dispatch of Units in Power Systems with Valve-Point Effects." *International Journal of Electrical and Computer Engineering* 4, No. 6, pp. 858, 2014.
- [17] J. Moradi, H. Shahinzadeh, A. Khandan, and M. Moazzami. "A Profitability Investigation into the Collaborative Operation of Wind and Underwater Compressed Air Energy Storage Units in the Spot Market." *Energy*, 2017.
- [18] C., Mingjian, J. Zhang, H. Wu, B.-Mathias Hodge, D. Ke, and Y. Sun, "Wind Power Ramping Product for Increasing Power System Flexibility." In *Transmission and Distribution Conference and Exposition (T&D), 2016 IEEE/PES*, pp. 1-5. IEEE, 2016.
- [19] H. Shahinzadeh, A. Gheiratmand, J. Moradi, and S. Hamid Fathi. "Simultaneous Operation of Near-To-Sea and Off-Shore Wind Farms with Ocean Renewable Energy Storage." In *Renewable Energy & Distributed Generation (ICREDG), 2016 Iranian Conference on*, pp. 38-44. IEEE, 2016.
- [20] M. Moazzami, Gevork B. Gharehpetian, H. Shahinzadeh, and S. H. Hosseini. "Optimal Locating and Sizing of Dg and D-Statcom using Modified Shuffled Frog Leaping Algorithm." In *Swarm Intelligence and Evolutionary Computation (CSIEC), 2017 2nd Conference on*, pp. 54-59. IEEE, 2017.
- [21] S. A. Mirjalili, S. M. Mirjalili, and A. Lewis. "Grey Wolf Optimizer." *Advances in Engineering Software* 69, pp. 46-61, 2014.
- [22] S. A. Mirjalili, "How Effective is the Grey Wolf Optimizer in Training Multi-Layer Perceptrons." *Applied Intelligence* 43, No. 1, pp. 150-161, 2015.
- [23] E. Emary, H. M. Zawbaa, and A. Ella Hassanien. "Binary Grey Wolf Optimization Approaches for Feature Selection." *Neurocomputing* 172, pp. 371-381, 2016.
- [24] P. Graf, Peter, G. Stewart, M. Lackner, K. Dykes, and P. Veers. "High-Throughput Computation and the Applicability Of Monte Carlo Integration In Fatigue Load Estimation Of Floating Offshore Wind Turbines." *Wind Energy* 19, No. 5, pp. 861-872, 2016.
- [25] M. Moazzami, S. J. Hosseini, and H. Shahinzadeh. "Optimal Sizing of an Isolated Hybrid Wind/PV/Battery System with Considering Loss of Power Supply Probability." *Majlesi Journal of Electrical Engineering* 11, No. 3, 2017.
- [26] H. Shahinzadeh, A. Gheiratmand, S. Hamid Fathi, and J. Moradi. "Optimal Design and Management of Isolated Hybrid Renewable Energy System (WT/PV/ORES)." In *Electrical Power Distribution Networks Conference (EPDC), 2016 21st Conference on*, pp. 208-215. IEEE, 2016.
- [27] H. Shahinzadeh, M. Moazzami, S. Hamid Fathi, and Gevork B. Gharehpetian. "Optimal Sizing and Energy Management Of A Grid-Connected Microgrid using HOMER Software." In *Smart Grids Conference (SGC)*, pp. 1-6. IEEE, 2016.
- [28] A. Kavousi-Fard, T. Niknam. "Multi-Objective Probabilistic Distribution Feeder Reconfiguration Considering Wind Power Plants." *International Journal of Electrical Power & Energy Systems* 55, pp. 680-691, 2014.
- [29] S. M. Mohseni-Bonab, A. Rabiee, S. Jalilzadeh, B. Mohammadi-Ivatloo, and S. Nojavan. "Probabilistic Multi Objective Optimal Reactive Power Dispatch Considering Load Uncertainties using Monte Carlo Simulations." *Journal of Operation and Automation in Power Engineering* 3, No. 1, pp. 83-93, 2015.
- [30] A. Daneshi, N. Sadrmomtazi, M. Khederzadeh, and J. Olamaei. "Integration of Wind Power and Energy Storage in SCUC Problem." In *World Non-Grid-Connected Wind Power and Energy Conference (WNWEC), 2010*, pp. 1-8. IEEE, 2010.
- [31] M. Shahidehpour, H. Yamin, and Z. Li. "Market Overview in Electric Power Systems." *Market Operations in Electric Power Systems: Forecasting, Scheduling, and Risk Management*, pp. 1-20, 2002.