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A Hybrid Method for Solving Unit Commitment Problem with Wind Power Uncertainty

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Abstract: In the paper, a hybrid method is proposed to solve the Unit Commitment (UC) problems incorporating with wind power system under uncertainty. The hybrid model is the combination of modified Bat algorithm and the Artificial Neural Network (ANN) technique with Genetic Algorithm (GA). The ANN technique is predicted the wind power generation based on the historical data of the wind power system using the GA. The modified Bat algorithm is the optimization algorithm that is optimizing the generating unit combination based on the load demand and the availability of the wind power from the ANN technique. Here, Gravitational Search Algorithm (GSA) is utilized to improve the searching behaviours of the Bat algorithm. The Bat algorithm considers thermal generators fuel cost, startup cost and wind power probability as the objective function. To achieve the objective function, the Bat algorithm requires to satisfying the constraints like thermal units generation constraints, spinning reserve constraints, startup cost constraints and ramp limit constraints. The proposed hybrid method based optimal generators combination is minimizing the thermal generators unit power generation cost by considering the wind power availability. The proposed hybrid method is implemented in MATLAB/Simulink working platform and the performance is evaluated. The proposed method is tested under standard 10 unit's system. In order to analyze the effectiveness of the proposed method, this is compared with the existing techniques such as, GA-ANN and Bat-ANN respectively. The performance of the proposed method is verified through the comparison analysis with the existing techniques. The comparison results prove the superiority of the proposed method.

Keywords: UC, ANN, GA, Bat, GSA, wind power probability, fuel cost and starting-up cost.

1. INTRODUCTION

The cumulative request of energy resources and the non-renewability of outdated energies make energy catastrophe one among the most considerate issues in the ecosphere [1]. And yet, the characteristic volatility of wind power inescapably transports about technological and economic trials to wind power incorporation. Wind power forecasting (WPF) skill is one among the most significant methods to alleviate negative influence from wind power volatility [2]. The ever-increasing diffusion of wind power transports encounters to the electricity market, as wind power is neither completely dispatch able nor fully expectable [3]. Infiltration of renewable energy resources into power schemes meaningfully surges the suspicions on scheme operation, stability and reliability in smart grids [4, 5]. Wind combined with the electrical power grid conveys numerous encounters to grid operators like operational issues upholding scheme frequency, power balance, voltage support, and quality of power, and also planning and economic forecasting anxieties [6].

By refining the forecasting accuracy, these assets can be abridged. Additionally, accurate wind speed/ power forecasting and solar irradiance predicting can progress the energy conversion effectiveness, decrease the menace produced using scheme overloading and exciting weather conditions and can progress the Unit Commitment (UC) optimization [7, 8]. Similar large-scale assumption grants numerous encounters to the operation of the electrical power grid due to the wind power is extremely recurrent and problematic to forecast. In specific, UC and economic dispatch (ED) procedures are inordinate reputations due to their durable economic influence and cumulative emissions anxieties [9, 10]. UC is a serious combinatorial optimization issue for daily economic planning and operation of the modern power scheme that cooperatively accomplishes appropriate on/ off decision of producing units and allocates produced power between the committed units to attain minimum generation cost while sustaining power claim, replacement and other rudimentary restraints over a programmed time horizon [11, 12].

The UC achieves a significant role in the operational planning of contemporary power scheme and protects important quantity of total operation cost per year [13, 14].An amended UC model seeing wind power indecision will progress to an improved UC result that can endure the forecast faults in the actual time [15, 16]. There are numerous heuristic and metaheuristic approaches for the wind power forecasting faults in the UC model like priority list technique, genetic algorithms (GA), tabu search algorithms (TS), particle swarm optimization algorithms (PSO), ant colony algorithms (ACO), fuzzy logic (FL) systems, artificial neural networks (ANN), evolutionary programming (EP) and simulated annealing (SA), mixed-integer linear programming (MILP), second order cone programming (SOCP), memetic algorithm (MA), bacterial foraging (BF), discrete differential evolution method [17, 18]. MILP technique has developed generally in current years due to more effectual general-purpose MILP solvers have become accessible. Though, MILP technique delivers a comparatively rough guesstimate for the UC issue [19, 20]. Here, the hybrid method is proposed to solve the unit commitment problem. The problem formulation and the detailed explanation of the suggested technique is offered in Section 3 and 4. Previous to that, the current research works are offered in Section 2. The experimental results and conversation are specified in Section 5. At last, the Section 5 shows result and discussions

2. RECENT RESEARCH WORKS: A BRIEF REVIEW

An insurance approach to refuge the conceivable imbalance cost that wind power producers may experience was discussed by Hongming Yang *et. al.* [21].

The power schemes face growing indecision from intermittent renewable resources was discussed by Joshua D.Lyon *et. al.* [22].

A methodology to resolve UC issue from a probabilistic viewpoint was discussed by J.M.Lujano-Rojas *et. al.* [23].

A method for generating clusters of the unit status connected to a probability of occurrence from a preliminary set of large wind power generation circumstances was deliberated by Anup Shukla *et. al.* [24].

The analysis of symmetry in UC issues resolved with the help of the Mixed Integer Linear Programming (MILP) formulations and by Linear Programming depended on Branch & Bound MILP solvers was deliberated by Ricardo M.Lima *et. al.* [25].

The UC problem comprises of defining optimal production strategy for a provided group of power plants over a specified time horizon so the complete production cost is decreased, by the meantime sustaining numerous restraints. Every power plant separately requires satisfying: minimum up time, minimum down time and production border constraints. The function of the conventional approaches is not acceptable if the objectives function/ constrains is intermittent and very multifaceted. To resolve the UC issue, some meta-heuristic approaches have been revealed that is appeal much more attention due to their aptitude to search local and global results and also easily dealing with numerous complex nonlinear constraints. The most extensively utilized meta-heuristic approaches such as ANN, GA, EP, SA, FL systems, PSO, and TS. The meta-heuristic approaches so far are not adequately supple for solving real world issues to optimality in satisfactory computational times, and it is tough to approximation the quality of the gotten solutions as they are stochastic search approaches. Hybrid approaches that syndicate the methods stated above (like GA combined with LR, PSO united with LR, Evolving Ant Colony Optimization (EACO) engages GA for detecting an optimal set of ACO parameters) incline to be more effectual than the discrete technique alone.

3. MULTI-OBJECTIVE BASED UNIT COMMITMENT PROBLEM

Mathematical formulation of the wind uncertainty based unit commitment problem related to the net load is described here. Generally, the unit commitment is an optimization problem that consists of minimizing the expected operating cost. This cost could be separated into fuel-consumption cost and starting-up cost. Conventionally, fuel-consumption cost has been modelled by employing a quadratic expression in terms of the related power production, while starting-up cost has been modelled by applying a piecewise expression that relies on the number of hours that a particular generator has been de-committed. The mathematical expression of the objective function is described in the following equation (1).

$$\mathrm{C} = \sum_{t=1}^{\mathrm{H}} \sum_{i=1}^{\mathrm{N}} \mathrm{PR}_{\mathrm{WT}}(j,t)\left\{a_i \mathrm{U}(i,t) + b_i \mathrm{P}_{\mathrm{TG}}(i,t)\mathrm{U}(i,t) + c_i \mathrm{P}_{\mathrm{TG}}^2(i,t)\mathrm{U}(i,t) + \mathrm{S}_c(i,t)\right\} \tag{1}$$

where, $\mathrm{S}_c(i,t) = k_{o,i}\left[1 - \exp\left(\frac{\mathrm{T}_{\mathrm{off}}(i,t)}{k_{1,i}}\right)\right] + k_{2,i}$

With, C is the total cost; H is the total number of hours; $\mathrm{U}(i, t)$ is the status of the unit i at t^{th} hour, i.e., 1 for ON and 0 for OFF; a_i, b_i and c_i are the fuel cost coefficients of the thermal generating unit i at t^{th} hour; $\mathrm{PR}_{\mathrm{WT}}(j, t)$ is the probability of the wind generator unit j at t^{th} hour, which is calculated based on wind power uncertainty; $\mathrm{P}_{\mathrm{TG}}(i, t)$is the output power of the thermal generator unit i at t^{th} hour; $\mathrm{S}_c(i, t)$ is the starting-up cost of unit i at t^{th} hour; N is the number of generating units; $k_{o,i}$, $k_{1,i}$ and $k_{2,i}$ are the starting-up cost coefficients of the thermal generating unit i and $\mathrm{T}_{\mathrm{off}}(i, t)$ is duration at which thermal generating unit i has been off at t^{th} hour. Working out the stochastic UC problem contains finding out the optimal combination of generators that should be entrusted and their related power production in order to minimize the generation costs over the scheduling horizon, considering the feasible fluctuations of the dissimilar sources of vagueness. The reported equation (1) depends on the thermal system constraints and wind power probability [26] [27] [28], which is described in the following.

Equality Constraints

Power balance constraints

$$\mathrm{P}_{\mathrm{TD}}(t) = \sum_{i=1}^{n} \mathrm{P}_{\mathrm{TG}}(i,t)\mathrm{U}(i,t) + \mathrm{P}_{\mathrm{WT}}^{\mathrm{ANN}}(j,t);\ \mathrm{U}(i,t) = 1 \tag{2}$$

where, $P_{TD}(t)$ is the total demand at period t; $P_{TGi}(i, t)$ is the power generated from thermal unit i at hour t; $P_{WT}^{ANN}(j, t)$ is the power generated from wind unit j at hour t, which is attained from the ANN.

Inequality Constraints

Spinning reserve constraints

$$\sum_{i=1}^{n} P_{TG}^{max}(i, t)U(i, t) - P_{TD}(t) \geq R(t) \tag{3}$$

where, $P_{TG}^{max}(i, t)$ is the maximum output power limit of the thermal unit i at hour t and $R(t)$ is the power system spinning reserve requirement at hour t.

Generating capacity constraints

$$P_{TG}^{min}(i, t) \leq P_{TG}(i, t) \leq P_{TG}^{max}(i, t) \tag{4}$$

Minimum up time limit

$$T_{on}(i, t) > Minup(t) \tag{5}$$

Minimum down time

$$T_{off}(i, t) > Mindown(t) \tag{6}$$

Ramp generation

$$P_{TG}(i, t) - P_{TG}(i, t-1) \leq R_U(i) \text{ as generation increases} \tag{7}$$

$$P_{TG}(i, t) - P_{TG}(i, t-1) \leq R_D(i) \text{ as generation increases} \tag{8}$$

where, $P_{TG}^{min}(i, t)$ and $P_{TG}^{max}(i, t)$ are the minimum and maximum power of thermal generating unit i at t^{th} hour; Minup(t) is the minimum up time of thermal generating unit at t^{th} hour; Mindown(t) is the minimum down time of thermal generating unit at t^{th} hour; $T_{on}(i, t)$ is duration at which thermal generating unit i has been on at t^{th} hour; RU(i) and RD(i) are the ramp up and down limit of the unit i. The overview of the proposed hybrid methodology is explained in the following section 4.

4. HYBRID METHOD FOR UNIT COMMITMENT PROBLEM

This section describes about the proposed hybrid methodology, which is the combined performance of ANN, modified bat algorithm. Here, the ANN is used to predict the wind power generation, which is used for the wind power probability calculation. The modified bat algorithm is used to optimize the generator unit combinations based on the wind power probability and load demand. The wind power generation prediction using ANN technique is described in the following section 4.1.

4.1. Enhanced ANN based Wind Power Generation Prediction

ANNs are a well approach for developing the mathematical structures with the ability to learn. It has the notable capability to derive meaning from complicated or indefinite data. This can be used help to extract patterns and detect trends that are excessively complex to be noticed by other techniques. Neural network generally consists of two stages namely, training and testing stage. It can be trained using many techniques. Back propagation (BP) algorithm is probably the most widely used ANN training technique in practical applications due to its inherent simplicity and ease of implementation [29] [30]. BP technique is based on gradient descent method. The concept is to have an error function and use hill climbing or descent to find the weights. This would optimize the task at hand. However studies have confirmed that back propagation is prone to the following problems – it may get stuck at a local optimum and it may take a very long time to converge. This led researchers to attack the ANN training problem with other methods. Another technique for ANN weight optimization is by using Genetic algorithms (GA). GA encodes the ANN weights as possible solutions for the problem in the chromosomes of simulated biological organisms. In each generation the organisms with best chromosomes are chosen for reproduction [31]. This continues for a predefined number of generations or until the problem is sufficiently optimized. GA has parallel search strategy and global optimization characteristics which helps the ANN to have a higher prediction accuracy and faster convergence compared to BP. However the genetic operators like crossover and mutation are inherently complex and hence make the computational cost to increase exponentially. The convergence speed of GA is better than BP. Therefore, in the paper, GA is used for training the ANN. Here, the wind power generation $\mathrm{P}_{\mathrm{WT}}^{\mathrm{ANN}}(j,t)$ can be recognized by the ANN technique. The learning task is specified in the form of examples, which is identified as training examples. The ANN turns out to be trained by employing the target with corresponding inputs, using the back propagation algorithm. The resultant wind power generation can be attained during the testing time. Normally the ANN have three layers that is given by,

(i) Input layer,

(ii) Hidden layer,

(iii) Output layer.

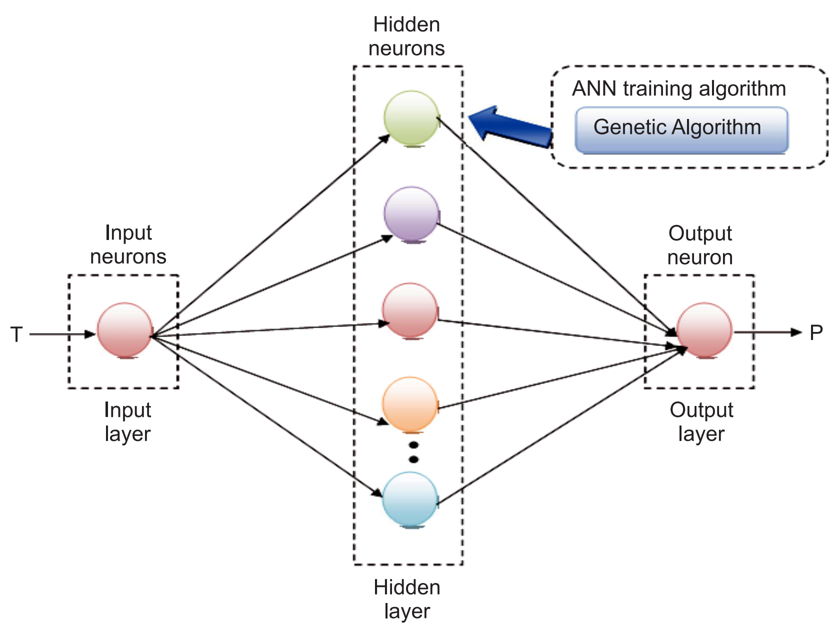

Figure 1: Structure of the enhanced ANN

Figure 1 shows the proposed ANN structure, which is trained by GA technique and observes the changes to prediction accuracy. The training algorithm steps are described as below. Here, the inputs are considered as the Y values and the weight of the network is assigned for input layer to hidden layer and hidden layer to output layer. From the input layer to hidden layer weights are denoted as (w_{11}, w_{12}, ..., w_{1n}), (w_{21}, w_{22}, ..., w_{2n}) and (w_{31}, w_{32}, ..., w_{3n}) respectively. The hidden layer to output layers weights are represented as (w_{211}, w_{221}, ..., w_{2n1}). The output of the node is specified as (P).

Process for Training Algorithm

Step 1: Initialize the weight of input layer, hidden layer and output layer of the network, which is specified as, Hour (T) and wind power generation $P_{WT}(j, t)$. Here, the weight of each neuron is assigned randomly for learning the network. The minimum and maximum weight (i.e., $W = (w_{min}, w_{max})$) of the interval range is specified as (0, 1).

Step 2: Studying the network according to the input and the related target.

Step 3: In the section, the BP error is determined. Here, the BP error is evaluated using the GA. In the GA, the optimized parameter of ANN is achieved while minimizing the BP error function.

Back propagation error minimization using GA technique: Genetic Algorithm is adaptive global search algorithm based on the evolutionary data of genetics. In order to work out the optimization problems Genetic Algorithm is an arbitrary search algorithm applied. Iterations are symbolized as generation and the population is symbolized as chromosomes in genetic algorithm [32]. Now the input of genetic algorithm is the consequence of test case generation. The specified process of genetic algorithm is made cleared beneath,

Initial Phase: In genetic algorithm, at first produce the population of chromosomes $E_i(i = 1, 2, 3, \ldots, N)$ randomly. N represents the population size.

Fitness Evaluation: Assess the fitness function of each chromosome and the highest fitness value is chosen as the best one.

Calculate the back propagation error using the following equation (9).

$$E_{BP}^{k} = P_{WT}(j,t)_k^{ANN(tar)} - P_{WT}(j,t)_k^{ANN(out)} \tag{9}$$

where, $P_{WT}(j,t)_k^{ANN(tar)}$ is the network target of the k^{th} node and $P_{WT}(j,t)_k^{ANN(out)}$ is the current output of the network. After that, evaluate their crossover and mutation rate.

Cross Over to the Best Solution: One or more parent chromosomes are selected and carry out the single point cross over.

Mutation: In mutation process chromosome values are differed according to the possibility after that produced novel chromosome.

Updation: In the process, the present chromosome is substituted with the best chromosome.

Discover the Fitness Function: If the fitness value of novel chromosome is greater than the present chromosome. Choose the novel chromosome is the best chromosome.

The maximum iteration is reached, then the process is terminated otherwise repeat the steps. Here, the minimized BP error values are calculated and their corresponding inputs are noted. Based on the fitness function, the ANN is optimally trained and gets the optimal outputs and the corresponding back propagation error of the network is calculated.

Step 4: The current output of the network is determined by using the following equation,

$$P_{WT}(j,t)_k^{ANN(out)} = \alpha_k + \sum_{n=1}^{N} w_{kn} P_{WT}(j,t)_k^{ANN}(n) \tag{10}$$

where, α_1, α_2 and α_k are the bias function of the node 1, 2 and k respectively.

$$P_{WT}(j,t)_k^{ANN}(n) = \frac{1}{1+\exp(-w_{kn}P_{WT}(j,t)_k - w_{1n}P_{WT}(j,t)_1)} \tag{11}$$

Step 5: The new weights of the each neurons of the network are updated by $w_{new} = w_{old} + \Delta w$. Here, w_{new} is the new weight, w_{old} is the previous weight and Δw is the change of weight of each output. The change of weight is determined as follows:

$$\Delta w_k = \delta \,.\, P_{WT}(j,t)_k \,.\, E_{BP}^k \tag{12}$$

where, δ is the learning rate (0.2 to 0.5).

Step 6: Repeat the above steps till the E_{BP}^k gets minimized $E_{BP}^k < 0.1$.

Repeat the above steps till the BP_{error} gets minimized $BP_{error} < 0.1$. Once the neural network training process is completed, the network is ready to give the wind power generation at the particular instant. Based on the wind power generation, the wind power probability for the particular instant has been calculated [33]. The optimal generator combination selection using the Bat-GSA algorithm is described in the following section.

4.2. Modified Bat Algorithm for Optimal Generator unit Combination Selection

In the paper, the modified bat algorithm is utilized to optimize the generating unit combinations. The hybrid algorithm is the combined operation of both the Bat algorithm and gravitational Search Algorithm (GSA) technique. In the proposed method, combined Bat-GSA algorithm finds the optimal combination of the generator units based on the objective function, which is possible by taking the generation limits of the generator as the input. Here, the solution updating process can be done by the GSA process. From the attained updated solutions, the best solution can be selected by using the objective function. The algorithmic procedure to find the optimal generator combination is described as follows.

4.2.1. Modified Bat Algorithm

The bat inspired algorithm constitutes an innovative optimization approach, which takes its cues from the echolocation conduct of the bats. In echolocation, each pulse produced by a microbat generally exists only for 8–10 ms with a frequency in the range of 25 kHz to 150 kHz, in accordance with the wavelengths of two mm to 14 mm. In the BA, the echolocation attributes of the Microbats are idealized by means of the stipulations detailed below [34-37].

(a) It is supposed that the bats are competent to identify the distance of the prey, background hazards and distinction in the accessible prey/food in the search path with certain magical skills by means of the echolocation attribute.

(b) A k^{th} Bat is likely to arbitrarily fly with location as x_k, velocity as v_k, frequency as f_{min} but with changing wavelength and loudness of echo as A_0 to locate the food/prey. The Microbats are equipped with the requisite skills of adapting the frequency (wavelength) of the emanated pulses of the echo and the rate of pulse emission out of R_e [0, 1] based on the distance of their prey/food.

(c) The loudness of the echo pulse has to be invariable changed in such a way as to decrease in the case of reduced distance of the food, in other words from a mammoth A_0 to a smallest value A_{min} (at target/ prey location).

In the document, the bat inspired algorithm is elegantly employed to allocate the units in the generating station. The input are considered as the generation limits of thermal generators X_i and arbitrarily produced for appraising the objective function, which constitutes the total operating cost (C) minimization. Subsequently, their corresponding parameters of the system are estimated as per the objective function. By means of the optimal results, the optimal C is estimated. The procedures for the optimization of the unit commitment of the system and the minimization of the C is explained in the following section.

Working Process

Step 1: Initialization process

(a) Here, the generation limits of thermal generators are initiated on the input of bat algorithm and this population is activated as position (P_k) and velocity (V_k) vector as with $k = 1, 2, 3, ..., n$. Subsequently, the pulse frequency (f_k), pulse rates (R_k) and loudness (A_k) are described. The range of initial frequency is represented as $f_k \in [f_{\min}, f_{\max}]$.

(b) The generating units are arbitrarily produced as $X_i = (x_1, x_2, x_3, ..., x_n)$

Step 2: Generate new solutions

In this procedure, the pulse rate and loudness are defined. Now, the new solutions are produced by adapting the pulse frequency and maintaining wavelength stable. For each bat (k), its position P_k and velocity V_k in a d-dimensional search space has to be well-explained. Afterwards, the P_k and V_k have to be modified during the iterations. The new solutions P_k^t and velocities V_k^t at time step t are evaluated by means of the following equations.

$$f_k = f_{\min} + (f_{\max} - f_{\min})\beta \tag{13}$$

$$V_k^t = V_k^{t-1} + (P_k^{t-1} - P')\, f_k \tag{14}$$

$$P_k^t = P_k^{t-1} + P_k^t \tag{15}$$

In the above-mentioned equations, β is represented for uniform distribution as a vector and chosen as $\beta \in [0, 1]$. P′ indicates the best location in the search space when the solutions of all the k^{th} bats are assessed and contrasted. The product of f_k and P_k signifies the velocity increment, which may be adapted by modifying one and preserving the other as constant in relation to a problem. The commonly employed range of frequency is $0 \le f \le 100$ and each bat at initialization step is chosen from $f = [f_{\min}, f_{\max}]$.

Step 3: Local Search: In this procedure, the pulse rate and loudness of the bats are appropriately defined. After the best current solution is chosen from among the accessible solutions, a new solution is created by means of a local arbitrary walk and allocated to each bat as illustrated in the equation furnished below. If $\varepsilon \in [-1, -1]$ signifies an arbitrary number range and $A^t = (A_k^t)$ corresponds to the average value of loudness of all activated n bats at time t.

$$P_{nw} = P_{\text{old}} + \varepsilon \times A^t \tag{16}$$

Step 4: Fitness evaluation: In this procedure, the fitness is defined as the objective function. And the total operating cost minimization is treated as the fitness function and their corresponding parameters are estimated.

$$F_i = \min(T_c) \tag{17}$$

Step 5: Bat flying and generation of a new solutions: In accordance with enhancement in the number of iterations, the loudness A_k and the rate R_k of pulse emission are modernized. When the microbat arrives near the target/prey the rate of pulse emission gets perked up while the loudness is reduced. The loudness is habitually chosen from $[A^0, A_{\min}] = [1, 0]$. The expression $A^0 = 1$, characterizes the maximum loudness of the pulse emanated by the microbat on the lookout for the prey, while $A_{min} = 0$ illustrates that the microbat is in possession of the target/prey and does not produce any loudness. Thus, the loudness and the rate of pulse emission are changed for updating process, which is illustrated in the following Equations.

$$A_k^{t+1} = \alpha A_k^t \tag{18}$$

$$R_k^{t+1} = R_k^0[1 - e^{-\gamma t}] \tag{19}$$

where, α and γ signify the constant values. The initial loudness and the emission rate are characterized by A_k^0 and R_k^0 correspondingly. The value of emission rate at time t may be chosen from $R_k^0 \in [0, 1]$.

If we allow the algorithm to switch to exploitation stage too quickly by varying A_k^0 and R_k^0 too quickly, it may lead to stagnation after some initial stage. As a novel feature, bat algorithm (BA) was based on the echolocation features of microbats, and BA uses a frequency-tuning technique to increase the diversity of the solutions in the population, while at the same, it uses the automatic zooming to try to balance exploration and exploitation during the search process by1mimicking the variations of pulse emission rates and loudness of bats when searching for prey. As a result, it proves to be very efficient with a typical quick start. Therefore, this paper intends to review the latest developments of the bat algorithm. Here, the performance of Bat algorithm is improved by utilizing the GSA algorithm with updating the parameter. The detailed description of GSA algorithm is explained as follows,

GSA for Updating the Solutions of BAT Algorithm: GSA is a newly developed stochastic search algorithm based on the law of gravity and mass interactions. In GSA, the search agents are a collection of masses which interact with each other based on the Newtonian gravity and the laws of motion, completely different from other well-known population-based optimization method inspired by swarm behaviours in nature [38] [39] [40]. GSA is used for improving the performance of Bat algorithm and updating the Bat parameters. Here, the inputs are considered as the agents. The minimized cost functions can be evaluated from the inputs. The optimal outputs are determined based on evaluated inputs. The procedure of the proposed algorithm is briefly explained as follows:

Procedure of Proposed Algorithm:

1. In the section, the Bat updating parameters are initiated randomly. Here, the inputs are considered as the agents. The position of agents are defined by the following equation,

$$S = (s_i^1, ..., s_i^d, ... s_i^n) \tag{20}$$

where, n is the search space dimension of the problem, s_i^d is the position of the i^{th} agent in the d^{th} dimension.

2. The fitness function of agents is evaluated as their minimum range of BP error. The minimized error function of the network is given to the network. The fitness function of the agent is calculated as follows:

$$F_i = \min(C) \tag{21}$$

After that, force of the agent is calculated.

3. The mass of agents are defined randomly and determine the forces of each agent. Here, the force acting on mass i from mass j can be determined by,

$$f_{ij}^d(k) = g(t)\left(\frac{M_i(k) \times M_j(k)}{r_{ij}(k) + \in}\right)\left(s_j^d(k) - s_i^d(k)\right) \tag{22}$$

where, $M_i(k)$ and $M_j(k)$ are masses of the agent i and j. Here, $g(k)$ is the gravitational constant, $\in$ is the small constant and $r_{ij}(k)$ is the Euclidian distance between i^{th} and j^{th} agents. Calculate the gravitational constant of the agent using the following formula,

$$g(k) = g_0 \times e^{\left(\frac{-\alpha k}{t_r}\right)} \tag{23}$$

From the above equation, t_r are the total iterations of the algorithm, g_0 is the initial value and α is the user specified constant.

4. The total force acts on the agent in k^{th} dimension is calculated as follows,

$$f_i^d(kt) = \sum_{i=1,\, j \neq i}^{N} \text{rand}_i f_{ij}^d(k) \tag{24}$$

where, rand_j is a random number in the interval [0, 1] and the acceleration is calculated.

5. Acceleration of any mass is equal to the force acted on the system divided by mass of inertia

$$\alpha_i^d(k) = \frac{f_i^d(k)}{M_i(k)} \tag{25}$$

6. New positions of the agents and gravitational constant & inertia masses are updated by the following equations.

$$m_i(k) = \frac{\text{fit}_i(k) - \text{worst}(k)}{\text{best}(k) - \text{worst}(k)} \tag{26}$$

$$M_i(k) = \frac{m_i(k)}{\sum_{j=1}^{N} m_j(k)} \tag{27}$$

where, $\text{fit}_i(k)$ represents the fitness value of the i^{th} agent at iteration k.

7. Velocity of each mass is calculated, the new position of the masses could be considered. Updating the agent's velocity and position using the following equation,

$$V_i^d(k+1) = \text{rand} \times v_i^d(k) + \alpha_i^d(k) \tag{28}$$

When acceleration and velocity of each mass are calculated then new positions of the masses could be considered as follows

$$s_i^d(k+1) = s_i^d(k) + v_i^d(k+1) \tag{29}$$

where, $V_i^d(k)$ and $s_i^d(k)$ are the velocity and position of an agent at the k time and d dimension, random_i is the random number at the interval at [0, 1].

8. The maximum iteration is reached, then the process is terminated otherwise repeat the step3-8. Here, the minimized cost functions values are calculated and their corresponding inputs are noted. Based on the fitness function, the bat algorithm is updated optimally and gets the optimal outputs

Step 6: If the conditions ($f_i < f_j$) is satisfied, the new solution is accepted by perking up the pulse rate and scaling down the loudness.

Step 7: Checking the stopping criterion: If the maximum count of iterations is attained when the stopping standard is fulfilled, then the task of evaluation is stopped. Or else, return to steps 3 and 4 for the replication of the procedure. Once the process is completed, the network is ready to give the better generator units combination for different types of load demand. The flowchart for the proposed Bat-GSA algorithm is illustrated in Figure 2.

The proposed methodology is implemented in the MATLAB/Simulink platform and the effectiveness is analysed by comparison with different techniques. The detailed analysis of the proposed method is described in the following section.

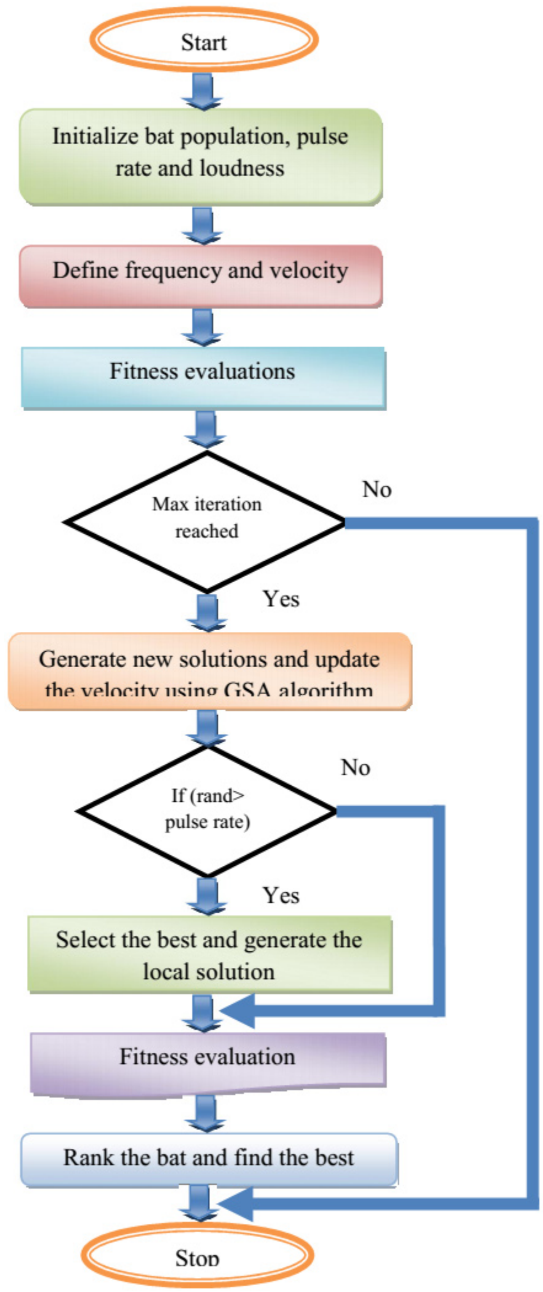

Figure 2: Flowchart of modified Bat algorithm

5. RESULTS AND DISCUSSION

In this paper, a hybrid method was utilized to solve the unit commitment problem in the power system. An enhanced ANN and modified Bat algorithm is worked as a hybrid technique. The performance of the proposed hybrid technique was tested with the unit system. The enhanced ANN is used to train the historical data of wind power at the 24 hours. Here, the Genetic Algorithm (GA) is carried out to train the ANN and enhance the performance of ANN. By using Bat algorithm, the optimal parameter of the unit system is determined. From the optimal values, the cost function of the unit system is evaluated. The updating function of Bat algorithm is updated by using the GSA. Based on the proposed algorithm, the minimum value of the fitness function is evaluated. A comparative analysis is performed between the proposed and existing techniques to demonstrate the effectiveness of the proposed method. The performance of proposed method is evaluated and compared with the GA-ANN and Bat-ANN techniques.

The implementation parameter of the proposed method is tabulated in Table 1.

Table 1
Implementation parameters

S.No.	*Description*	*Algorithms*	*Value*
1	W(min, max)	ANN	(0,1)
2	Number of Hidden layer		10
3	Population size	GA	50
4	Crossover rate		0.01
	Mutation rate		0.03
5	Population size	Bat	50
6	Loudness		1
7	Pulse rate		1
8	Qmin		0
9	Qmax		2
	Number of Generations		100
10	Number of agents	GSA	5
11	Rnorm		10

5.1. Performance Analysis of 10 unit System

In the sub section, the experimentation is carried out in test systems with ten generator units. Here, the Table 2 and 3 illustrates that the data used in the experimentation and describes the load demand for the UCP [41, 42]. The modified Bat algorithm is utilized for solving the UCP in the system. The system parameters such as generation limits, cost coefficients, startup cost, and unit minimum ON and OFF time are used. The optimization of thermal generators combination and performance based on 24 hours load demand profile of the system. Allocating the generator incurs both fuel cost and startup cost in order to satisfy the load demand. Hence, the total operating cost for a thermal generator allocation is calculated that is a sum of both fuel cost and start up cost.

Table 2
Description of the Ten Unit System under Analysis

No	P_{min} *(MW)*	P_{max} *(MW)*	*a* *($/h)*	*b* *($/MWh)*	*c* *($/MW^{2}h)*	T_{on} *(h)*	T_{off} *(h)*	*DR* *(MW/h)*	*UR* *(MW/h)*	*IS* *(h)*	*CSC* *($)*	*HSC* *($)*	*CST* *($)*
1	150	455	1000	16.19	0.00048	8	8	130	130	8	9000	4500	5
2	150	455	970	17.26	0.00031	8	8	130	130	8	10000	5000	5

No	P_{min} *(MW)*	P_{max} *(MW)*	*a* *($/h)*	*b* *($/MWh)*	*c* *($/MW^{2}h)*	T_{on} *(h)*	T_{off} *(h)*	*DR* *(MW/h)*	*UR* *(MW/h)*	*IS* *(h)*	*CSC* *($)*	*HSC* *($)*	*CST* *($)*
3	25	162	450	19.7	0.00398	–6	6	90	90	-6	1800	900	4
4	20	130	680	16.5	0.00211	–5	5	60	60	-5	1120	560	4
5	20	130	700	16.6	0.002	–5	5	60	60	-5	1100	550	4
6	20	80	370	22.26	0.00712	–3	3	40	40	-3	340	170	2
7	20	80	370	22.26	0.00712	–3	3	40	40	-3	340	170	2
8	25	85	480	27.74	0.00079	–3	3	40	40	-3	520	260	2
9	25	85	480	27.74	0.00079	–3	3	40	40	-3	520	260	2
10	10	55	660	25.92	0.00413	–1	1	40	40	-1	60	30	0

Table 3
Load demand for 24 hours

Hour	*Load demand (MW)*	*Hour*	*Load demand (MW)*
1	700	13	1400
2	750	14	1300
3	850	15	1200
4	950	16	1050
5	1000	17	1000
6	1100	18	1100
7	1150	19	1200
8	1200	20	1400
9	1300	21	1300
10	1400	22	1100
11	1450	23	900
12	1500	24	800

Table 4
Thermal generator unit's status

Unit	*Time (h)*																							
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	0	0	1	0	1	0	1	0	0
4	0	0	1	0	0	0	1	0	0	1	1	1	1	1	0	0	1	0	1	1	0	0	1	0
5	1	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	0	0	0
6	0	0	0	0	0	0	0	0	1	0	1	1	0	0	1	1	0	0	0	0	1	0	0	0
7	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	1	0	1	0	0
8	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	1	0	0	0	0

Table 5
Power dispatch of the generator units

Hour	Units power dispatch (MW)									
	1	2	3	4	5	6	7	8	9	10
1	445.98	0	0	0	152.32	0	0	0	0	0
2	410.92	264.59	0	0	0	0	0	0	0	0
3	400.02	334.42	0	13.59	0	0	0	0	0	0
4	451.52	448.31	0	0	0	0	0	0	0	0
5	414.31	399.21	0	0	127.64	0	0	0	0	0
6	339.21	435.76	110.02	0	141.05	0	0	0	0	0
7	423.78	413.69	0	107.51	110.84	0	0	0	0	0
8	376.34	440.28	113.21	0	149.42	0	0	0	46.38	0
9	447.01	428.95	115.99	0	149.34	56.97	0	0	0	0
10	423.03	404.96	129.01	109.52	155.97	0	74.76	45.09	0	0
11	450.96	450.32	118.94	120.03	155.68	79.21	0	0	0	43.37
12	445.91	449.98	126.95	122.24	130.07	76.32	77.24	0	0	0
13	409.94	436.82	114.82	98.93	149.92	0	0	0	0	37.96
14	451.23	374.86	108.74	115.07	142.93	0	0	53.08	0	0
15	438.28	410.54	104.23	0	118.24	59.06	0	0	0	0
16	453.37	421.98	0	0	0	71.53	0	0	0	0
17	425.59	348.35	0	128.43	0	0	0	0	0	0
18	451.64	448.04	128.01	0	0	0	0	0	0	0
19	441.6	440.24	0	120.99	0	0	79.42	0	0	0
20	445.36	430.13	115.03	122.04	143.01	0	77.08	0	0	38.10
21	453.38	453.14	0	0	154.04	66.08	0	0	0	51.05
22	421.98	407.21	113.21	0	0	0	45.43	0	0	0
23	360.82	341.32	0	79.46	0	0	0	0	0	0
24	423.7	369.24	0	0	0	0	0	0	0	0

Table 6
Wind probability for 24 hours

Hour	Wind probability	Hour	Wind probability
1	0.8269	13	0.9502
2	0.8730	14	0.9547
3	0.8816	15	1
4	0.8373	16	0.8976
5	0.9250	17	0.9430
6	0.8930	18	0.8884
7	0.9425	19	0.9401
8	0.9207	20	1
9	0.9624	21	0.9133
10	1	22	0.9289
11	0.9630	23	0.9721
12	0.9552	24	0.9033

In the ANN technique, the wind and load demands are trained. We assume that the uncertain wind power output follows a multivariate normal distribution with the forecasted value. To generate each individual historical data sample, we use ANN training for getting optimal outputs. Based on the wind probability and load demands, the modified Bat algorithm is utilized to get the optimal solution. The generator units are scheduled using the proposed method as per the load variation and the wind probability. The Table 4 indicates the on/off status of the generators for 24 hours using the binary variables. The generator is on at the particular instant, which is denoted as 1 otherwise 0. The scheduled thermal generators are allowed to generate the power based on the wind power probability. The required generator power using proposed method based on the wind power probability at 24 hours is described in Table 5. Here, the multi-objective function plays an important role, because it minimizes the fuel cost and start-up cost. The wind power probability for 24 hours is illustrated in Table 6, which varies between 0.8269 and 1.

Table 7
Cost parameters of the scheduled generator units

Time (h)	*Fuel cost ($)*	*Starting-up cost ($)*	*Total cost ($)*
1	11482.24	0	11482.24
2	13081.31	0	13081.31
3	15043.04	0	15043.04
4	17060.21	0	17060.21
5	18253.31	0	18253.31
6	20714.07	450	21164.07
7	21157.14	0	21157.14
8	23703.53	1140	24843.53
9	24416.18	0	24416.18
10	29204.19	1410	30614.19
11	30101.37	0	30101.37
12	30144.86	0	30144.86
13	22220.07	50	22270.07
14	23141.08	0	23141.08
15	21204.05	270	21474.05
16	16142.34	0	16142.34
17	16410.42	0	16410.42
18	20046.04	0	20046.04
19	21096.89	1240	22336.89
20	29104.89	2560	31664.89
21	24264.96	320	24584.96
22	20110.07	1420	21530.07
23	15125.31	1040	16165.31
24	15040.96	0	15040.96

It is used to analyze the power dispatch of unit system according to their desired constraints. Depending on the wind power generation, the thermal generator cost has been minimized. The cost parameters attained from the given generator schedule is illustrated in Table 7, which shows the fuel cost, start-up cost and the total cost. Table 7 gives power dispatch details of the ten – unit system along with the startup cost and fuels cost for 24 hours. Table 8 gives the details of the sum of total operating cost incurred, when testing with different techniques. The 24 hour load demand is given in Figure 3. Based on the objective function, the generator allocation with the amount of power dispatching is performed. However, the combination of generator units is optimized by the proposed technique to minimize the cost for load demand conditions.

Table 8
Comparison results for 10 unit system

Techniques	*Minimum Operating cost ($)*
ELR[43]	563977
GA[44]	565825
SA[45]	565828
UCC-GA[46]	563977
QEA-UC[47]	563938
ICA[48]	563938
NSGA-II+DLS[49]	563938
GA-ANN	523214.3
BAT-ANN	516347.9
Proposed hybrid technique	508168.5

From the illustrations, we can understand that the first hour utilizes the minimum operating cost of $11482.24 at the load demand 700MW and the wind probability is 0.8269. The maximum operating cost of $ 31664.89 is attained from the 20th hour at the load demand 1400MW and the wind probability is 1. Then the effectiveness of the proposed method is compared with the GA-ANN and Bat-ANN techniques and the other methodologies available in the literature. The total cost attained from the different techniques is described in Table 8. The cost comparison is graphically illustrated in Figure 4, which clearly shows that the proposed method effectively selects the optimal generating unit combinations with reduced cost compared to the other techniques.

The convergence characteristics of the proposed method compared with the GA-ANN and Bat-ANN have been described in Figure 5. The convergence performance is analyzed for 100 numbers of iterations.

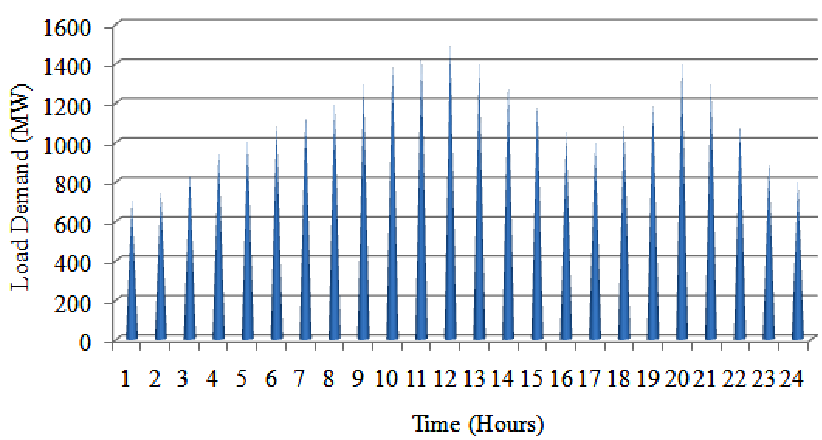

Figure 3: Load demand for 24 hours

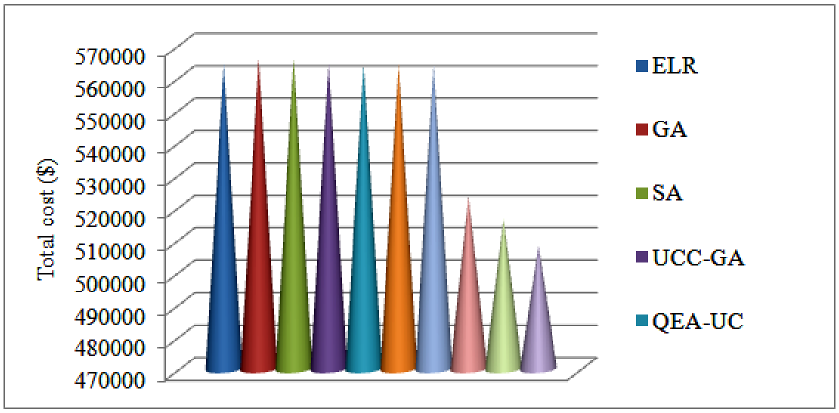

Figure 4: Total operating cost of different approaches

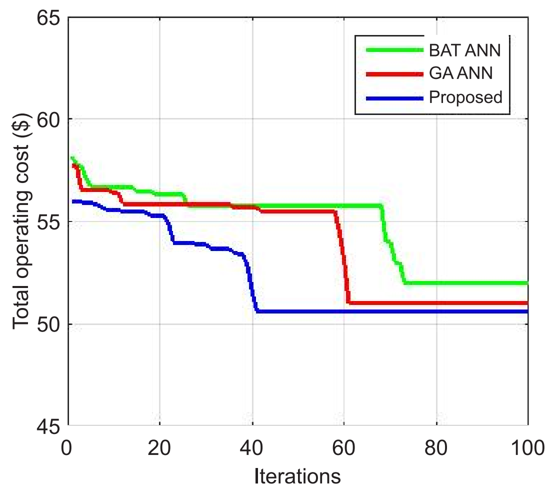

Figure 5: Convergence characteristics of the different approaches

Hence, it can be demonstrated that the proposed method is more effective than the existing methods in solving the unit commitment problem.

6. CONCLUSION

In this paper, we briefly analysed about the hybrid technique which was proposed for solving the UCP in the system. The hybrid technique is the combination of enhanced ANN and modified Bat algorithm. Here, GA was used for training the ANN and enhancing their performance. Bat algorithm was utilized to minimize the total operating cost of unit system. Here, the ten unit system was considered, which contains the wind power probability, system and generating unit constraints. The proposed method was implemented in Matlab/Simulink platform. Using the proposed algorithm, the optimized the cost function of UCP are determined. The performance of the proposed method is evaluated and compared with the existing methods such as, GA-ANN and Bat-ANN respectively. The proposed technique was regularly employed to produce the useful solutions, which are competent enough for scheduling generators with large scale constraints to work out large scale optimization problems. The proposed hybrid algorithm obtained lesser cost than other methods available in the literature, when validated on the ten-unit test systems. The validation results have proved the dominating performance of the proposed methodology over the other techniques that are reported in the literature.

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