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An Adaptive Modified Firefly Algorithm to Unit Commitment Problem for Large-Scale Power Systems

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Abstract- *Unit commitment (UC) problem tries to schedule output power of generation units to meet the system demand for the next several hours at minimum cost. UC adds a time dimension to the economic dispatch problem with the additional choice of turning generators to be on or off. In this paper, in order to improve both the exploitation and exploration abilities of the firefly algorithm (FA), a new modification approach based on the mutation and crossover operators as well as an adaptive formulation is applied as an adaptive modified firefly algorithm (AMFA). In this paper, it is shown that AMFA can solve the UC problem in a better manner compared to the other meta-heuristic methods. The method is applied on some case studies, a typical 10-unit test system, 12, 17, 26, and 38 generating unit systems, and IEEE 118-bus test system, all with a 24-hour scheduling horizon. Comparison of the obtained results with the other methods addressed in the literature shows the effectiveness and fastness of the applied method.*

Keyword: Adaptive modified firefly algorithm, Optimization in power system, Power generation scheduling, Unit commitment problem.

NOMENCLATURE

t / T	Index/set for time
i	Index for units
$\alpha_i, \beta_i, \gamma_i$	Fuel cost coefficients for *i*th unit
N	Total number of power generation units
HSC_i	Hot start-up cost of *i*th unit
CSC_i	Cools start-up cost of *i*th unit
T_i^D	Minimum down time of unit *i*
CST_i	Cold start time of unit *i*
MD_i^{on}	The number of hours that *i*th unit has been on-line since it was turned on
MD_i^{off}	The number of hours that *i*th unit is off-line since it has been turned off
D^t	The load (MW)
SR^t	Spinning reserve (MW) at time *t*
T_i^U	Minimum up time of unit *i*
u_i^t	Electricity market Price ($/kWh)
P_i^t	Total planning horizon
F_i	Capacity limit of *k*th DG technology (kW)

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1. INTRODUCTION

The lifestyle of a modern man follows regular habits, and hence the present society also follows regularly repeated cycles or pattern in daily life. Therefore, the consumption of electrical energy also follows a predictable daily, weekly and seasonal pattern. There are periods of high-power consumption as well as low power consumption. It is possible to commit the generating units from the available capacity into service to meet the demand. For a given combination of plants, the determination of optimal combination of plants for operation at any one time is also desired for carrying out the aforesaid task. The plant commitment and unit ordering schedules extend the period of optimization from a few minutes to several hours. From daily schedules, weekly patterns can be developed. Likewise, monthly, seasonal and annual schedules can be prepared to take into consideration the repetitive nature of the load demand and seasonal variations. Unit commitment schedules are thus required for economically committing the units in plants to service with the time at which individual units should be taken out from or returned to service. The power-generation industry utilizes unit commitment (UC) and economic dispatch to help make generation scheduling decisions. In a UC problem, decisions about which units to interconnect are made for the day-ahead market.

Independent system operators (ISO) are responsible for coordinating, controlling and monitoring the operation of power systems [1]. Most ISOs today run the UC problem 24 hours before the real-time market. The objective of a running a UC problem is to identify a schedule of committing units to minimize the joint cost of UC and economic dispatch, while at the same time meet the forecasted demand. After determination of the committed units, economic dispatch (ED) sub-problem should be solved. ED sub-problem is solved to specify optimal generation of each on-line unit to reach minimum operational cost [2, 3].

In recent years, many computational techniques have been proposed to solve the problem. The applied methods for solving this problem are divided into two categories. The first is mathematical, and the second is heuristic/meta-heuristic approaches [4]. The mathematical optimization models find an optimum expansion plan by using a calculation procedure that solves a mathematical formulation of the problem. Due to the impossibility of considering all aspects of the UC problem, the plan obtained is the optimum only under some simplifications and should be technically, from a financial standpoint and environmentally verified, among other alternatives, before the planner makes a decision. Since UC is a large scale, non-convex and mixed-integer non-linear combinatorial optimization problem, several solutions techniques have been proposed in the literature. Exhaustive enumeration may give an exactly optimal solution but time consuming, while a priority list may have a fast solution that sometimes leads to a non-optimal outcome. Dynamic programming (DP) is a well-known solution technique for UC problem. Its solution is correct and has the optimal value; it takes a lot of memory and takes a lot of time in getting an optimal solution.

Priority list-based [5], branch and bound, Lambda logic algorithm [6], Mixed integer linear programming (MILP) [7, 8], benders decomposition [9], stochastic priority list (SPL) [10], Lagrange relaxation (LR) [11], enhanced adaptive Lagrange relaxation (ELR) and adaptive Lagrange relaxation (ALR) [12], dynamic programming Lagrange relaxation (DP-LR) [12], combination of LR and linear programming [13], and extended priority list (EPL) [14], were applied to solve UC problem. These techniques are well known mathematical solution techniques for the UC problem that needs more computational efforts. The heuristic methods are the current alternative of mathematical optimization models. The term “heuristic” is used to describe all those techniques that, instead of using a classical optimization approaches, go step-by-step generating, evaluating and selecting expansion options, with or without the user’s help.

Application of heuristic optimization algorithms may have some advantages to solve such a complicated optimization problem, while the main drawback of these methods is that they cannot guarantee the global optimal solution. Recently, some meta-heuristic techniques have been addressed like genetic algorithm (GA) [15, 16], whale optimization algorithm (WOA) [17], floating point GA (FPGA) [18], matrix real coded genetic algorithm (MRCGA) [19], unit characteristic classification genetic algorithm (UCC-GA) [20], binary coded genetic algorithm (BCGA) and integer coded genetic algorithm (ICGA) [21], ant colony search algorithm (ACSA) [22], tabu search (TS) [23], tabu search random perturbation (TS-RP) and tabu search improved random perturbation (TS-TRP) [24], particle swarm optimization (PSO) [25], hybrid particle swarm optimization (HPSO) [26], binary particle swarm optimization (BPSO) [27], improved particle swarm optimization (IPSO) [28], simulated annealing (SA) [29], gravitational search algorithm (GSA) [30], imperialistic competition algorithm (ICA) [31], shuffled frog leaping algorithm (SFLA) [32], bacterial foraging (BF) [33], differential evolution (DE) [34], evolutionary programming (EP) [35], and memetic algorithm (MA) [36]. Since there exist a need for more improvement to the existing unit commitment solution techniques, the hybrid models such as hybrid neural network and simulate annealing, fuzzy adaptive PSO (FAPSO) [37], HSA and numerical optimization [38], fuzzy dynamic programming (FDP) [39], genetic-based artificial neural network (GANN) [40], hybridization of Lagrange relaxation and genetic algorithm (LRGA) [41], PSO combined with LR (PSO-LR) [42], simulated annealing genetic algorithm (SAGA) [43] and priority list-based evolutionary algorithm [44], hybrid improved firefly algorithm with PSO (IFA-PSO) [45], FA with multiple workers [46], binary real coded firefly algorithm (BRCFA) [47, 48], Lagrangian firefly algorithm (LFA) [49] are experienced. Firefly algorithm has been applied in many fields of electrical power system. Ref. [50] proposes a method to minimize the real power loss of a power system transmission network using FA by optimizing the control variables such as transformer taps, UPFC location and UPFC series injected voltage magnitude and phase angle. Ref. [51] focuses on investigating the optimum values of Power System Stabilizer (PSS) parameters by the implementation FA based optimization technique. In Ref. [52], transformer routine tests have been analyzed by using the generated

FA. In Ref. [53], to overcome the difficulties in solving the non-convex and mixed integer nature of transmission expansion planning problem, the FA is applied to solve the problem. Ref .[54] attempts to develop an optimal hybrid energy system model using available solar and wind energy resources with battery storage for fulfilling the electrical needs of three un-electrified remote villages located in Senapati district of Manipur, India, so, The FA based approach is used to find the optimal hybrid system configuration based on minimum cost of energy. In Ref. [55] a novel approach to determining the feasible optimal solution of the economic dispatch problem using FA has been presented. In Ref. [56], improved FA is applied to determine the optimum switching angles for the 11-level cascaded H bridge multilevel inverter with adjustable DC sources in order to eliminate pre specified lower order harmonics and to achieve the desired fundamental voltage. Ref. [57] presents a new and hybrid algorithm based on FA and recursive least square for power system harmonic estimation. In Ref. [58], a novel FA optimized hybrid fuzzy PID controller with derivative filter is proposed for load frequency control of multi area multi source system under deregulated environment. Ref. [59] proposes a FA to solve optimal power flow (OPF) in power system which has a unified power flow controller. In [60] a hybrid FA and pattern search optimized fuzzy PID controller is proposed for Load frequency control of multi area power systems. Ref. [61] presents an enhanced FA for solving multi-objective optimal active and reactive power dispatch problems with load and wind generation uncertainties. In Ref. [62], economic load dispatch problem is discussed and implemented with FA optimization technique to obtain the best optimal solution for the fuel cost of generator. In Ref. [63], a novel hybrid FA and pattern search technique is proposed for a static synchronous series compensator based power oscillation damping controller design. Ref. [64] presents the implementation of the FA with an online wavelet filter on the automatic generation control model for a three unequal area interconnected reheat thermal power system. Ref. [65] presents multi-objective economic emission dispatch solution using hybrid FA with considering wind power penetration.

In this paper, the authors focus on applying the AMFA, to solve the UC problem, dealing with continuous as well as discrete variables. In fact, the applied modification approach helps the firefly algorithm by increasing the diversity of the fireflies in the population. Also, since in the UC problem some variables are binary, the discrete-variable form of AMFA is used to solve such problem. Comparing the simulation results from this study with those reported from other studies reveals that the AMFA is a more effective technique than other approaches in the literature from both the operation costs and computational time aspects.

This paper is organized as follows: Section 2 formulates the UC problem. Section 3 presents the applied optimization technique and its application to solve the UC problem. Section 4 conducts the numerical simulations and presents a comparison among different methods used to solve the UC problem. Finally, concluding remarks are discussed in Section 5.

2. PROBLEM FORMULATION

UC involves determining generating outputs of all units from an initial hour to meet load demands associated with a start-up and shut-down plan over a time horizon. The objective function is to find the optimal scheduling such that the total operating costs can be minimized while satisfying the load demand, spinning reserve requirements as well as other operational constraints. The objective function of the UC problem is a function that comprises the fuel costs of generating units, the start-up costs of the committed units and shut-down costs of the decommitted units. The objective function in a common form is formulated as:

$$\text{Min} \sum_{i=1}^{N}\sum_{t=1}^{T}\left[F_i(P_i^t)u_i^t + \text{SUC}_i u_i^t (1-u_i^{t-1})\right] \tag{1}$$

where:

$$F_i(P_i^t) = \alpha_i + \beta \times P_i^t + \gamma \times (P_i^t)^2 \tag{2}$$

The start-up cost is defined as follow:

$$SUC_i^t = \begin{cases} HSC_i\,, & if\ T_i^D \le MD_i^{on} \le T_i^D + CST_i\,, \\ & 1 \le t \le T, i \in N \\ CSC_i\,, & if\ MD_i^{on} > T_i^D + CST_i \end{cases} \tag{3}$$

The objective function in Eq. (1) is subjected to constraints. The generated real power must be sufficient enough to meet the load demand. This constraint is given by Eq. (4).

$$\sum_{i=1}^{N} P_i^t u_i^t = D^t \quad 1 \le t \le T\,, i \in N \tag{4}$$

Spinning reserve (SR) is usually a pre-specified amount or equal to the largest unit or a given percentage of the forecasted load demand. Spinning reserve of committed units is the total amount of real power generation available from all synchronized units minus the present load plus the losses. It must be sufficient enough to maintain the desired reliability of a power system. Spinning reserve constraint, unit output limits, minimum up time limit and minimum down time limit are given by Eqns. (5-8) receptively.

$$\sum_{i=1}^{N} P_i^{\max} u_i^t \geq D^t + SR^t \ , \ \ i \in N \tag{5}$$

$$P_i^{\min} u_i^t \leq P_i^t u_i^t \leq P_i^{\max} u_i^t \ , \ \ 1 \leq t \leq T, \ i \in N \tag{6}$$

$$MD_i^{on} \geq T_i^U \ , \ \ i \in N \tag{7}$$

$$MD_i^{off} \geq T_i^D \ , \ \ i \in N \tag{8}$$

3. FIREFLY ALGORITHM

According to the flashing light of fireflies is an amazing sight in the summer sky in the tropical and temperate regions. There are about two thousand firefly species, and most fireflies produce short and rhythmic flashes. The pattern of flashes is often unique for a particular species. The flashing light is produced by a process of bioluminescence, and the true functions of such signaling systems are still debating. However, two fundamental functions of such flashes are to attract mating partners (communication), and to attract potential prey. In addition, flashing may also serve as a protective warning mechanism. The rhythmic flash, the rate of flashing and the amount of time form part of the signal system that brings both sexes together. Females respond to a male’s unique pattern of flashing in the same species, while in some species such as photuris, female fireflies can mimic the mating flashing pattern of other species so as to lure and eat the male fireflies who may mistake the flashes as a potential suitable mate. We know that the light intensity at a particular distance *r* from the light source obeys the inverse square law. That is to say, the light intensity *I* decrease as the distance *r* increases in terms of $I \propto (1/r^2)$. Furthermore, the air absorbs light which becomes weaker and weaker as the distance increases. These two combined factors make most fireflies visible only to a limited distance, usually several hundred meters at night, which is usually good enough for fireflies to communicate. The flashing light can be formulated in such a way that it is associated with the objective function to be optimized, which makes it possible to formulate new optimization algorithms. In the rest of this paper, we will first outline the basic formulation of the FA and then discuss the implementation bas well as its analysis in detail. Now we can idealize some of the flashing characteristics of fireflies so as to develop firefly-inspired algorithms. For simplicity in describing our new FA, we now use the following three idealized rules:

```
Objective function f(x),        x = (x1, ..., xd)^T
Generate initial population of fireflies xi (i = 1, 2, ..., n)
Light intensity Ii at xi is determined by f(xi)
Define light absorption coefficient   γ
while  (t <MaxGeneration)
for i = 1 : n all n fireflies
for j = 1 : i all n fireflies
if (Ij > Ii), Move firefly i towards j in d-dimension; end if
Attractiveness varies with distance r via exp[−γr]
Evaluate new solutions and update light intensity
end for j
end for i
Rank the fireflies and find the current best
end while
Postprocess results and visualization
```

Fig. 1. Pseudo code of the firefly algorithm

- All fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex;
- Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less bright one will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brighter one than a particular firefly, it will move randomly;
- The brightness of a firefly is affected or determined by the landscape of the objective function. For a maximization problem, the brightness can simply be proportional to the value of the objective function. Other forms of brightness can be defined in a similar way to the fitness function in GA. Based on these three rules, the basic steps of the FA can be summarized as the pseudo code shown in Fig. 1.

In certain sense, there is some conceptual similarity between the FA and the bacterial foraging algorithm (BFA). In BFA, the attraction among bacteria is based partly on their fitness and partly on their distance, while in FA; the attractiveness is linked to their objective function and monotonic decay of the attractiveness with distance. However, the agents in FA have adjustable visibility and more versatile in attractiveness variations, which usually leads to higher mobility and thus the search space is explored more efficiently.

In the FA, there are two important issues: the variation of light intensity and formulation of the attractiveness. For simplicity, we can always assume that the attractiveness of a firefly is determined by its brightness which in turn is associated with the encoded objective function. In the simplest case for maximum optimization problems, the brightness *I* of a firefly at a particular location x can be chosen as $I(x) \propto f(x)$. However, the attractiveness β is relative; it should be seen in the eyes of the beholder or judged by the other fireflies. Thus, it will vary with the distance r_{ij} between firefly i and firefly j. In addition, light intensity decreases with the distance from its source, and light is also absorbed in the media, so we should allow the attractiveness to vary with the degree of absorption. In the simplest form, the light intensity *I(r)* varies according to the inverse square law $I(r) = I_s / r^2$, where, I_s is the intensity at the source. For a given medium with a fixed light absorption coefficient γ, the light intensity I varies with the distance r. That is $I = I_0 e^{-\gamma r}$, where I_0 is the original light intensity. In order to avoid the singularity at $r = 0$ in the expression I_s / r^2, the combined effect of both the inverse square law and absorption can be approximated using the following Gaussian form as in Eq. (9).

$$I(r) = I_0 e^{-\gamma r^2} \tag{9}$$

The distance between any two fireflies i and j at x_i and x_j, respectively, is the Cartesian distance as in Eq. (10).

$$r_{ij} = \left\| x_i - x_j \right\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{10}$$

where, $x_{i,k}$ is the kth component of the spatial coordinate x_i of ith firefly. In 2-D case, the distance is in Eq. (11).

$$r_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{11}$$

The movement of a firefly i is attracted to another more attractive (brighter) firefly j is determined by following equation:

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2} (x_j - x_i) + \alpha(rand - \frac{1}{2}) \tag{12}$$

Where, the second term is due to the attraction while the third term is randomization with α being the randomization parameter. The rand is a random number generator uniformly distributed between 0 and 1. For most cases in this implementation, $\beta_0 = 1$. Furthermore, the randomization term can easily be extended to a normal distribution N(0,1) or other distributions. In addition, if the scales vary significantly in different dimensions such as −105 to 105 in one dimension while, say, −0.001 to 0.01 along the other, it is a good idea to replace α by αS_k where the scaling parameters Sk(k = 1, ..., d) in the d dimensions should be determined by the actual scales of the problem of interest. The parameter γ now characterizes the variation of the attractiveness, and its value is crucially important in determining the speed of the convergence and how the FA behaves. In theory, $\gamma \in (0, \infty]$, but in practice, $\gamma = O(1)$ is determined by the characteristic length γ of the system to be optimized. Thus, in most applications, it typically varies from 0.01 to 100. According to [66] as many optimization problems involve a number of constraints that the decision solutions need to satisfy, the aim of constrained optimization is to search for feasible solutions with better objective values. Generally, a constrained optimization problem is to find x so as to:

$$\begin{aligned} &\min \;\; f(x), \quad x = (x_1, ..., x_n) \in R^n \\ &where \;\; x \in F \subseteq S \end{aligned} \tag{13}$$

The objective function f is defined on the search space $S \subseteq R^n$ and the set $F \subseteq S$ defines the feasible region. The search space S is defined as an n-dimensional rectangle in R^n. The variable domains are limited by their lower and upper bounds:

$$l_i \le x_i \le u_i, 1 \le i \le n \tag{14}$$

Whereas, the feasible region $F \subseteq S$ is defined by a set of m additional constraints (m ≥ 0):

$$\begin{aligned} &g_j(x) \le 0, \quad for\ j = 1, ..., q \\ &h_j(x) = 0, \quad for\ j = q+1, ..., m \end{aligned} \tag{15}$$

For an inequality constraint that satisfies $g_j(x)=0$, we will say that is active at x. All equality constraints h_j (regardless of the value of x used) are considered active at all points of F. Both the objective function and the constraints can be linear or nonlinear. We incorporated the three simple selection criteria based on feasibility into the firefly algorithm to guide the search to the feasible region.

- When comparing two feasible solutions, the one with the better objective function is chosen.
- When comparing a feasible and an infeasible solution, the feasible one is chosen.
- When comparing two infeasible solutions, the one with the lower sum of constraint violation is chosen.

The sum of constraint violation for a solution x is given by:

$$CV(x) = \sum_{j=1}^{q} \max(0, g_j(x)) + \sum_{j=q+1}^{m} \left| h_j(x) \right| \tag{16}$$

Hence, the decision what firefly is more attractive is made according these feasibility rules. The FA does not start with the feasible initial population, since initialization with feasible solutions is hard and in some cases impossible to achieve randomly. During running process of FA, the feasibility rules direct the solutions to feasible region.

In every iteration, a variation of the feasibility-based rule was applied to compare the solution associated with every individual firefly *i* with every other firefly *j*. The rule is given below.

- If both fireflies are at feasible positions and firefly *j* is at better position than firefly *i* then firefly *i* moves towards firefly *j*.
- If firefly *i* is at an infeasible position and firefly *j* is at a feasible position then i moves to firefly *j*.
- If positions of firefly *i* and firefly *j* are infeasible and number of constrains satisfied by firefly *j* are more than that of firefly *i* then firefly *i* moves to firefly *j*.
- Once the position of the firefly is updated using above rules 1 to 3, if the updated position of the firefly *i* presents improved solution over the solution associated with its previous iteration position, then firefly *i* accepts its current solution, else retains its previous iteration solution.

In order to improve the FA search ability as well as reducing the local optima trapping possibilities, an adaptive modified firefly algorithm (AMFA) is presented [67]. There exist two main ideas in this modification. First, improving the population diversity by the aid of two mutations and three cross over operations; Second, encouraging the total firefly population to move toward the best promising local or global individual. Furthermore, in each iteration the total firefly population should be improved as explained in the following paragraph.

Assume X_{Best}^{Iter} and X_{worst}^{Iter} as the best and the worst individual of the firefly population in each iteration, respectively. For the *i*th firefly in the population, three fireflies X_{q1}, X_{q2} and X_{q3} are selected from the fireflies' population randomly such that $q_1 \neq q_2 \neq q_3 \neq i$. Two new individuals will be generated as [67]:

$$\begin{aligned} X_{Mute1} &= X_{q1} + \Delta \times (X_{q2} - X_{q3}) \\ X_{Mute2} &= X_{Mute1} + \Delta \times (X_{Best}^{Iter} - X_{worst}^{Iter}) \end{aligned} \tag{17}$$

Where, Δ is a random number laying in the range of $[0,1]$. The following fireflies are generated by utilizing the X_{Mute1} and X_{Mute2} . Now by the use of the X_{Mute1} and X_{Mute2} the following five fireflies are produced:

$$\begin{aligned} X_{Best,1} &= \left[\chi_{Best,1}, \chi_{Best,2}, \ldots, \chi_{Best,d} \right] \\ \chi_{\text{Im}\,prove1,j} &= \begin{cases} \chi_{Mute1,j} & \kappa_1 \leq \kappa_2 \\ \chi_{Best,j} & \kappa_1 > \kappa_2 \end{cases} \end{aligned} \tag{18}$$

$$\chi_{\text{Im}\,prove2,j} = \begin{cases} \chi_{Mute1,j} & \kappa_3 \leq \kappa_2 \\ \chi_j & \kappa_3 > \kappa_2 \end{cases} \tag{19}$$

$$\chi_{\text{Im}\,prove3,j} = \begin{cases} \chi_{Mute1,j} & \kappa_4 \leq \kappa_3 \\ \chi_j & \kappa_4 > \kappa_3 \end{cases} \tag{20}$$

$$\chi_{\text{Im}\,prove4,j} = \begin{cases} \chi_{Mute1,j} & \kappa_5 \leq \kappa_4 \\ \chi_{Mute2,j} & \kappa_5 > \kappa_4 \end{cases} \tag{21}$$

$$X_{\text{Im}\,prove5} = \psi \times X_{worst} + \zeta \times (X_{Best} - X_{Worst}) \tag{22}$$

where, $\kappa_1, \kappa_2, \kappa_3, \kappa_4, \kappa_5, \psi$ and ζ are random values laying in the range of $[0,1]$. The objective function is calculated for all of the above generated fireflies. The *i*th firefly will be replaced by the firefly with the smallest objective function. If the objective function value of the *i*th firefly is smaller than the best obtained firefly, then there will not be any replacement. The randomization parameter (α) is utilized in Eq. (12) in order to control the algorithm for a random search while the neighbouring fireflies are not seen by the given firefly. In fact, α manages the random movement of each firefly chosen randomly in the range of $[0,1]$. The large values of α result in the optimum solution search through the faraway search space, while a small α facilitate the local search. Thus, an appropriate value for the randomization parameter (α) leads to a satisfying balance between the global and the local search. To achieve this task, an adaptive control procedure is introduced in this paper to improve the total ability of the algorithm for both local and global search. Therefore, in this paper an adaptive control procedure is introduced to improve the ability of the algorithm for both the local and the global search. Moreover, this algorithm has been run several times and a different heuristic function for each iteration is obtained as follows [67]:

$$\alpha^{Iter+1} = \left(\frac{1}{2k_{\max}} \right)^{\frac{1}{k_{\max}}} \alpha^{Iter} \tag{23}$$

where, *Iter* is the iteration number and k_{max} is the maximum number of iterations. This function is employed during the optimization process to provide a sufficient balance between the local and global search by changing the value of α. According to Fig. 2, for handling integer variables, each firefly generates an initial solution randomly. For each firefly, find the brightest or the most attractive firefly. If there is a brighter firefly, then the less bright firefly will move towards the brighter one and if there is no brighter one than a particular firefly, it will move randomly.

```
Input:
Objective function f(x), x = (x1,... xd)T                          {cost function}
Initialize a population of fireflies xi (i = 1, 2, ..., n)
Define light absorption coefficient γ and number of moves m        {parameters}
Output:
xi min
begin
    for i = 1 to n do
        xi ⍰ Generate_Initial_Solution
    endfor
    repeat
        for i = 1 to n do
            xj ⍰ Find_Attractive_Firefly(xi)
            if (xj ≠ null) then
                Move_Firefly(xi, xj) for m times        {move firefly i towards j}
            else
                Move_Random(xi) for m times             {firefly i move randomly}
          endif
        endfor
        Select n brightest fireflies from (m x n) + 1
    until stop condition true
end
```

Fig. 2. Handling integer variables

When a firefly moves, existing solution produced by the firefly is changed. Each firefly move as much as *m* times. So, there will be (m ×n) + 1 fireflies at the end of iteration since only the best firefly will be included in selection process for the next iteration. Then, *n* best fireflies will be chosen based on an objective function for the next iteration. This condition will continue until the maximum iteration is reached.

4. NUMERICAL RESULTS

This section conducts two case studies consisting of the ten-unit test system, 12, 17, 26, 38 test cases and the IEEE 118-bus test system to illustrate the performance of the applied method. It should be noted that ramp rate constraint is considered only in the second test system and the first test system does not have this constraint.

4.1. 10-unit based problem

The formulation has been applied to solve a commonly used UC problem based on the ten-unit test system. This problem consists of a group of unit commitment problems. The basic problem includes ten units with a scheduling time horizon of 24 h. The 20-unit, 40-unit, and 100-unit UC problems are generated by scaling the generating units and load demand by 2, 4,…, and 10 times, respectively. The spinning reserve is held as 10% of the scaled load in each case. For quick reference, the hourly load distribution over 24-h time horizon and the generating unit's data are given in Tables 1 and 2, respectively. In order to show the impact of important control parameter in finding the optimum solution of the problem, α parameter changes within its permissible range.

For implementation of FA, first sensitivity analysis on the α parameter was done while the β and γ parameters set to value 1 because of the FA that applied in many researches, the β and γ parameters set to value of 1. The number of iterations for simulation is considered 10,000. To obtain optimal values for each parameter, the algorithm has been implemented 50 times and the best values of the objective function with its, mean and standard deviation has been presented in Table 3.

Table 1. Load demand of the 10-unit based problem

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

Table 2. Unit characteristics and cost coefficients of 10.unit system

Unit	P_i^{min}	P_i^{max}	α_i	β_i	γ_i	T_i^{on}	T_i^{off}	HSC_i	CSC_i	CST_i	IS
1	150	455	1000	16.19	0.00048	8	8	4500	9000	5	8
2	150	455	970	17.26	0.00031	8	8	5000	10000	5	8
3	20	130	700	16.6	0.002	5	5	550	1100	4	-5
4	20	130	680	16.5	0.00211	5	5	560	1120	4	-5
5	25	162	450	19.7	0.00398	6	6	900	1800	4	-6
6	20	80	370	22.26	0.00712	3	3	170	340	2	-3
7	25	85	480	27.74	0.00079	3	3	260	520	2	-3
8	10	55	660	25.92	0.00413	1	1	30	60	0	-1
9	10	55	665	27.27	0.00222	1	1	30	60	0	-1
10	10	55	670	27.79	0.00173	1	1	30	60	0	-1

Table 3. Sensitivity analysis for α parameter

α	Best	Average	Standard deviation
10 unit system			
0.1	563865	563874	6.03
0.5	564125	564137	5.14
1	563932	563948	5.34
10	563893	563902	4.18
20	**563865**	**563867**	**1.87**
50	563922	563934	4.47
100	564335	564347	5.13
20 unit system			
0.1	1122974	1122981	4.56
0.5	1122832	1122846	4.23
1	1122744	1122751	3.78
10	1122693	1122697	3.25
20	**1122622**	**1122625**	**2.11**
50	1122838	1122845	5.32
100	1122991	1122997	5.07
40 unit system			
0.1	2242393	2242399	3.26
0.5	2242365	2242368	3.25
1	2242324	2242329	3.25
10	2242293	2242296	3.25
20	2242235	2242239	3.26
50	**2242178**	**2242182**	**3.24**
100	2242209	2242216	3.36
60 unit system			
0.1	3363745	3363756	3.29
0.5	3363633	3363641	3.18
1	3363597	3363606	3.13
10	3363541	3363547	3.11
20	3363512	3363518	3.03
50	**3363491**	**3363494**	**3.02**
100	3363530	3363544	3.23
80 unit system			
0.1	4485928	4485939	4.14
0.5	4485870	4485891	4.14
1	4485848	4485857	4.10
10	4485792	4485801	4.11
20	4485703	4485729	4.11
50	**4485633**	**4485639**	**4.03**
100	4485702	4485723	4.38
100 unit system			
0.1	5605510	5605654	5.67
0.5	5605497	5605612	5.62
1	5605410	5605519	5.63
10	5605321	5605417	5.35
20	5605243	5605321	5.36
50	**5605189**	**5605211**	**5.34**
100	5605248	5605334	5.49

Table 4. Total cost ($) and execution time (sec) comparisons of different methods

No. of units	LR [5]		ICGA [4]		SPL [3]		MRCGA [2]		MA [1]	
	Total cost	Time (sec)	Total cost	Time	Total cost	Time	Total cost	Time	Total cost	Time
10	566107	257	566404	7.4	564950	7.24	564244	3.6	565827	290
20	1128362	514	1127244	22.4	1123938	16.32	1125035	12.6	1128192	538
40	2250223	1066	2254123	58.3	2248645	46.32	2246622	43.2	2249589	1032
60	3374994	1595	3378108	117.3	3371178	113.85	3367366	102.9	3370820	2740
80	4496729	2122	4498943	176	4492909	215.77	4489964	169.7	4494214	3159
100	5620305	2978	5630838	242.5	5615530	374.03	5610031	260.5	5616314	6365
No. of units	ALR [7]		GA [9]		PSO [8]		ELR [7]		LRGA [6]	
	Total cost	Time	Total cost	Time (sec)	Total cost	Time	Total cost	Time	Total cost	Time
10	565508	3.2	565825	221	574153	-	563977	4	564800	518
20	1126720	12	1126243	733	1125983	-	1123297	16	1122622	1147
40	2249790	34	2251911	2697	2250012	-	2244237	52	2242178	2165
60	3371188	67	3376625	5840	3374174	-	3363491	113	3371079	2414
80	4494487	111	4504933	10036	4501538	-	4485633	209	4501844	3383
100	5615893	167	5627437	15733	5625376	-	5605678	345	5613127	4045
No. of units	IPSO [8]		BPSO [11]		PSO-LR [5]		FPGA [10]		DP-LR [7]	
	Total cost	Time	Total cost	Time	Total cost	Time	Total cost	Time	Total cost	Time
10	-	-	565804	-	565869	42	564094	-	564049	108
20	125279	-	-	-	1128072	91	1124998	-	1128098	299
40	2248163	-	-	-	2251116	213	2248235	-	2256195	1200
60	3370979	-	-		3376407	360	3368375	-	3384293	3199
80	4495032	-	-	-	4496717	543	4491169	-	4512391	8447
100	5619248	-	-	-	5623607	730	5614357	-	5640488	12437
No. of units	EPL [12]		PLEA [14]		BCGA [4]		UCC-GA [13]		HPSO [12]	
	Total cost	Time	Total cost	Time	Total cost	Time	Total cost	Time	Total cost	Time
10	563977	0.72	563977	-	567367	3.7	563977	85	563942	-
20	1127256	2.97	1124295	-	130291	15.9	1125516	225	-	-
40	2252612	11.9	2243913	-	2256590	63.1	2249715	614	-	-
60	3376255	23	3363892	-	3382913	137	3375065	1085	-	-
80	4505536	44.4	4487354	-	4511438	257	4505614	1975	-	-
100	5633800	64.5	5607904	-	5637930	397	5626514	3547	-	-
No. of units	EP [16]		ACSA [15]		DP [9]		FA		AMFA	
	Total cost	Time	Total cost	Time	Total cost	Time	Total cost	Time	Total cost	Time
10	565352	100	564049	-	565825	-	563977	3	563865	2.62
20	1127256	340	-	-	-	-	1124715	26	1122622	24
40	2252612	1176	-	-	-	-	2248740	81	2242178	78
60	3376255	2267	-	-	-	-	3371064	162	3363491	157
80	4505536	3584	-	-	-	-	4495414	238	4485633	233
100	5633800	6120	-	-	-	-	5615407	323	5605189	316

Table 5. Units output power for the 10-unit case

Unit	Hour																							
	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	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455
2	245	295	370	455	390	360	410	455	455	455	455	455	455	455	455	310	260	360	455	455	455	455	420	345
3	0	0	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0	0
4	0	0	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0	0
5	0	0	25	40	25	25	25	30	85	162	162	162	162	85	30	25	25	25	30	162	85	145	25	0
6	0	0	0	0	0	0	0	0	20	33	73	80	33	20	0	0	0	0	0	33	20	20	0	0
7	0	0	0	0	0	0	0	0	25	25	25	25	25	25	0	0	0	0	0	25	25	25	0	0
8	0	0	0	0	0	0	0	0	0	10	10	43	10	0	0	0	0	0	0	10	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	10	10	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0

Table 6. Total cost ($) and execution time (sec) comparisons of different methods for 12, 17, 26 and 38 test cases

No. of units	Control Parameter		Total cost		Time	
	β_0	γ	AMFA	Ref [17]	AMFA	Ref [17]
12	0.4	1	639897.36	639938.60	147.23	153
17	0.9	0.5	1013998.76	1014390	150.38	157
26	0.9	0.9	582933.38	582938	442.12	473
38	0.4	1.5	197081933.65	197082680	570.36	603

Table 7. Load demand of the IEEE 118-bus test system

Hour	Load (MW)	SR (MW)	Hour	Load (MW)	SR (MW)
1	4200	210	13	4800	240
2	3960	198	14	4560	228
3	3480	174	15	5280	264
4	2400	120	16	5400	270
5	3000	150	17	5100	255
6	3600	180	18	5340	267
7	4200	210	19	5640	282
8	4680	234	20	5880	294
9	4920	246	21	6000	300
10	5280	264	22	5400	270
11	5340	267	23	5220	261
12	5040	252	24	4920	246

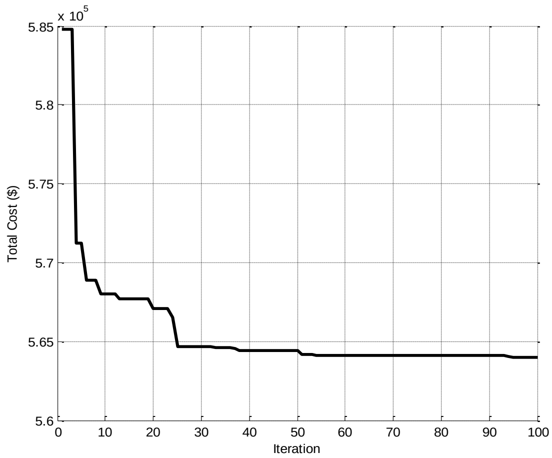

Fig. 3. Optimization procedure by AMFA for the 10-unit-based UC problem

Table 8. Unit characteristics and cost coefficients of IEEE 118-bus test system

Unit	$P_i^{\min}$	$P_i^{\max}$	α_i	β_i	γ_i	T_i^{on}	T_i^{off}	SUC_i	IS
1	5	30	0.069663	26.2438	31.67	1	1	40	1
2	5	30	0.069663	26.2438	31.67	1	1	40	1
3	5	30	0.069663	26.2438	31.67	1	1	40	1
4	150	300	0.010875	12.8875	6.78	8	8	440	8
5	100	300	0.010875	12.8875	6.78	8	8	110	8
6	10	30	0.069663	26.2438	31.67	1	1	40	1
7	25	100	0.012800	17.8200	10.15	5	5	50	5
8	5	30	0.069663	26.2438	31.67	1	1	40	1
9	5	30	0.069663	26.2438	31.67	1	1	40	1
10	100	300	0.010875	12.8875	6.78	8	8	100	8
11	100	350	0.003000	10.7600	32.96	8	8	100	8
12	8	30	0.069663	26.2438	31.67	1	1	40	1
13	8	30	0.069663	26.2438	31.67	1	1	40	1
14	25	100	0.012800	17.8200	10.15	5	5	50	5
15	8	30	0.069663	26.2438	31.67	1	1	40	1
16	25	100	0.012800	17.8200	10.15	5	5	50	5
17	8	30	0.069663	26.2438	31.67	1	1	40	1
18	8	30	0.069663	26.2438	31.67	1	1	40	1
19	25	100	0.012800	17.8200	10.15	5	5	59	5
20	50	250	0.002401	12.3299	28	8	8	100	8
21	50	250	0.002401	12.3299	28	8	8	100	8
22	25	100	0.012800	17.8200	10.15	5	5	50	5
23	25	100	0.012800	17.8200	10.15	5	5	50	5
24	50	200	0.004400	13.2900	39	8	8	100	10
25	50	200	0.004400	13.2900	39	8	8	100	10
26	25	100	0.012800	17.8200	10.15	5	5	50	5
27	100	420	0.010590	8.3391	64.16	10	10	250	10
28	100	420	0.010590	8.3391	64.16	10	10	250	10
29	80	300	0.010875	12.8875	6.78	8	8	100	10
30	30	80	0.045923	15.4708	74.33	4	4	45	4
31	10	30	0.069663	26.2438	31.67	1	1	40	1
32	5	30	0.069663	26.2438	31.67	1	1	40	1
33	5	20	0.028302	37.6968	17.95	1	1	30	1
34	25	100	0.012800	17.8200	10.15	5	5	50	5
35	25	100	0.012800	17.8200	10.15	5	5	50	5
36	150	300	0.010875	12.8875	6.78	8	8	440	10
37	25	100	0.012800	17.8200	10.15	5	5	50	5
38	10	30	0.069663	26.2438	31.67	1	1	40	1
39	100	300	0.003000	10.7600	32.96	8	8	440	10
40	50	200	0.010875	12.8875	6.78	8	8	400	10
41	8	20	0.028302	37.6968	17.95	1	1	30	1
42	20	50	0.009774	22.9423	58.81	1	1	45	1
43	100	300	0.010875	12.8875	6.78	8	8	100	8
44	100	300	0.010875	12.8875	6.78	8	8	100	8
45	100	300	0.010875	12.8875	6.78	8	8	110	8
46	8	20	0.028302	37.6968	17.95	1	1	30	1
47	25	100	0.012800	17.8200	10.15	5	5	50	5
48	25	100	0.012800	17.8200	10.15	5	5	50	5
49	8	20	0.028302	37.6968	17.95	1	1	30	1
50	25	50	0.009774	22.9423	58.81	2	2	45	2
51	25	100	0.012800	17.8200	10.15	5	5	50	5
52	25	100	0.012800	17.8200	10.15	5	5	50	5
53	25	100	0.012800	17.8200	10.15	5	5	50	5
54	25	50	0.009774	22.9423	58.81	2	2	45	2

The standard FA can be considered as a generation to PSO, DE and SA. From Eq. (12), one can see that when β0 is zero, the updating formula becomes essentially a version of parallel SA, and the annealing schedule controlled by α. On the other hand, if we set γ=0 in Eq. (12) and set β0=1 (or more generally, $\beta_0 \in$ Uniform (0,1), FA becomes a simplified version of DE without mutation, and the crossover rate is controlled by β0. Furthermore, if we set γ=0 and replace xj by the current global best solution g*, then Eq. (12) becomes a variant of PSO, or accelerated PSO, to be more specific. Therefore, the standard FA includes DE, PSO and SA as its special cases. As a result, FA can have all the advantage of these three algorithms. Consequently, it is no surprised that FA can perform very efficiently. This program has been operated on a computer with Intel Core i7, 2.53 CPU and 8 GB RAM. The results of applying 27 different methods to the ten-unit system and its multiples were taken directly from , tabulated and compared with the results obtained from our method in Table 4 from the viewpoints of total operating cost and execution time. This table summarizes the total cost of different UC solving techniques that consists of production and start-up costs. As shown in this table, for the case with ten units, the used method gives the best result, and for the other cases, the method came up with the total costs that are less than that of many other methods while very close to the least costs. Also execution times of different UC solving methods are presented in this Table. Although the CPU times shown in Table (4) may not be directly comparable due to different computers or programming languages used, but some insight can be gained. It is obvious that except for the ten-unit case, our run times are significantly lower than the run times of all other methods. The 21.3 s that we obtained for 100-unit case is less than one third of the next least CPU time. Therefore, the applied method is efficient and suitable for large-scale practical cases. Table 5 gives the 24-h units outputs for the ten-unit case. Fig. 3 shows convergence characteristic for the 10-unit-based UC problem by AMFA. As it can be seen, the AMFA has rapid convergence characteristic.

4.2. 12, 17, 26, and 38-unit systems

The AMFA is tested on 12, 17, 26, and 38 unit systems. The necessary data of these cases are in [47]. In all cases, the ON/OFF status of the generating units is obtained using the applied algorithm. Good convergence behavior can be achieved if the control parameters, namely β_0 and γ and can be optimally tuned. The optimal tuning of these firefly parameters like section 4.1 is tuned and the results are shown in Table 6. As can be seen, the used approach yields a better quality solution with less computational time.

4.3. IEEE 118-bus system

The IEEE 118-bus system consisting of 54 units is considered to study using the AMFA method. The data for this system are given in Tables 7 and 8. All the constraints involved in this problem are regarded, and a more practical constraint is considered that is: each committed unit must be scheduled to operate at its lower generation limit in the first and last hours of being committed. Table 9 presents the units' output powers for 24-h time horizon with a total operating cost of $1643818 $ and execution time of 6.57 s.

Table 9. Units output power (MW) for the IEEE 118-bus test system

Units	Hour																							
	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	203	180	150	150	150	150	203	270	255	270	270	264	225	195	270	270	270	270	285	300	300	270	270	255
5	200	180	140	100	100	160	200	260	240	280	280	260	240	200	280	280	277	280	280	300	300	280	280	240
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	25	40	40	25	25	25	40	40	25	40	55	62.5	70	40	40	25
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	200	180	140	100	100	157	200	260	240	280	280	260	240	200	280	280	260	280	280	300	300	280	280	240
11	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	25	40	40	25	25	25	40	40	25	40	55	62.5	70	40	40	25
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	25	40	40	25	25	25	40	40	25	40	55	62.5	70	40	32	25
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	25	40	40	25	25	25	40	40	25	40	55	62.5	70	40	25	25
20	250	250	250	134	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250
21	250	250	250	130	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250
22	0	0	0	0	0	0	0	0	25	40	40	25	25	25	40	40	25	40	55	62.5	70	40	25	25
23	0	0	0	0	0	0	0	0	25	40	40	25	25	25	40	40	25	40	55	62.5	70	40	25	25
24	200	200	100	155	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200
25	200	200	100	151	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200
26	0	0	0	0	0	0	0	0	25	32	40	25	25	25	32	40	25	40	55	62.5	70	40	25	25
27	420	488	356	178	292	356	420	420	420	420	420	420	420	420	420	420	420	420	420	420	420	420	420	420
28	420	488	356	178	292	356	420	420	420	420	420	420	420	420	420	420	420	420	420	420	420	420	420	420
29	212	189	124	80	80	146	212	256	256	278	278	256	234	205	278	278	278	278	278	300	300	278	278	256
30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	25	25	40	25	25	25	25	40	25	40	55	62.5	70	40	25	25
35	0	0	0	0	0	0	0	0	25	25	40	25	25	25	25	40	25	40	55	60	70	40	25	25
36	195	180	150	150	150	150	195	264	244	270	270	255	225	195	270	270	270	270	285	300	300	270	270	244
37	0	0	0	0	0	0	0	0	25	25	40	25	25	25	25	40	25	40	55	55	67.5	40	25	25
38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
39	300	300	300	300	300	300	300	300	300	300	300	300	300	300	300	300	300	300	300	300	300	300	300	300
40	200	185	125	50	80	155	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
43	200	180	140	100	100	140	200	260	240	280	280	260	231	200	280	280	260	280	280	300	300	280	280	240
44	200	180	129	100	100	140	200	260	240	280	280	260	220	200	280	280	260	280	280	300	300	280	280	240
45	200	180	120	100	100	140	200	260	240	280	280	260	220	200	280	280	260	280	280	300	300	280	280	240
46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	25	25	32	25	25	25	25	40	25	32	55	55	62.5	40	25	25
48	0	0	0	0	0	0	0	0	25	25	25	25	25	25	25	40	25	25	54.5	55	62.5	40	25	25
49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	25	25	25	25	25	25	25	40	25	25	47.5	55	62.5	40	25	25
52	0	0	0	0	0	0	0	0	25	25	25	25	25	25	25	40	25	25	47.5	55	62.5	40	25	25
53	0	0	0	0	0	0	0	0	25	25	25	25	25	25	25	32	25	25	47.5	55	62.5	32	25	25
54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

5. CONCLUSION

This paper presents a new method the so-called AMFA, for the unit commitment problem as well as scheduling problem. The applied approach is successfully used to well known test systems, 10-unit-based system and its multiples, 12, 17, 26 and 38 test systems, and also IEEE 118-bus. The significant results are compared with the other methods from both total operating costs and computational time aspects. Simulation results confirm that the AMFA may achieve better results. In the 10-unit-based system the AMFA gives the best results for both total costs and execution time among different methods. For example, in 10-unit system, the total cost is improved 0.27%, 0.46%, 0.18%, 0.09% 0.2, 0.21%, 0.4%, 0.01%, 0.14%, 0.33%, 0.63%, 0.51%, 0.58%, 0.38%, 0.51% than LR, ICGA, SPL, MRCGA, MA, ALR, GA, ELR, LRGA, PSO-LR, DP-LR, EPL, BCGA, UCC-GA, EP method, respectively, and, the execution time is improved 89.39%, 15.52%, 95.04%, 98%, 8.41%, 92.19%, 56.71%, 97.46%, 20.4%, 91.1%, 94.84% than LR, SPL, MA, GA, ELR, LRGA, PSO-LR, DP-LR, BCGA, UCC-GA, EP method, respectively. Results for the IEEE 118-bus test system show that AMFA is a cost-effectiveness technique that may also improve the reliability of power systems. Also results show the usefulness of the used method which is capable of solving both small-scale and large-scale power systems UC as well as scheduling problems.

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