Optimal Generation Scheduling Considering Distributed Generator for Cost Minimization based on Adaptive Modified Firefly Algorithm

Sujono
Electrical Engineering Department
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
Electrical Engineering Department
Universitas Budi Luhur
Jakarta, Indonesia
sujono@budiluhur.ac.id

Ardyono Priyadi
Electrical Engineering Department
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
priyadi@ee.its.ac.id

Margo Pujiantara
Electrical Engineering Department
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
margo_pujiantara@yahoo.com

Sjamsjul Anam
Electrical Engineering Department
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
anam@ee.its.ac.id

Naoto Yorino
School of Engineering, Hiroshima University, Japan
yorino@hiroshima-u.ac.jp

Mauridhi Hery Purnomo
Computer Engineering Department,
Institut Teknologi Sepuluh Nopember,
Surabaya, Indonesia
hery@te.its.ac.id

2021 International Electronics Symposium (IES) | 978-1-6654-4346-3/21/$31.00 ©2021 IEEE | DOI: 10.1109/IES53407.2021.9594032

***Abstract*— The increasing load and the decreasing availability of non-renewable energy sources have encouraged the development of renewable energy utilization. This condition increases the complexity of the power system. Distributed generator (DG) connection causes a significant change in power flow. On the other hand, the load on the power system is dynamic, so it is necessary to adjust the power generation. Proper scheduling of generating units to improve the reliability of the power system is crucial. Scheduling optimization is the key in power system operation planning and control to achieve optimal power system operation, with minimal cost and power loss. This paper presents the optimization of generating unit scheduling by applying the Adaptive Modified Firefly Algorithm (AMFA). The performance of AMFA in optimizing generator scheduling for minimal generation costs and power losses is tested by using a modified IEEE 30-bus system. The simulation results show that AMFA has a better performance than the firefly algorithm (FA), with a convergence speed of 4 times faster. Additionally of optimization by applying a distributed generator shows an improvement in the condition of the bus voltage in the system, lower costs, and power losses. In a system without DG which is loaded with 130% baseload, the optimization results indicate that 67% of the buses are under voltage, the generation cost is 1458.702 $/hour and the power loss is 23.345 MW. The integration of DG into the system is able to improve the system where only 3% of the buses are under voltage, the cost of generating 1143.111 $/hour, and power loss 1333.521 MW.**

***Keywords*—modified firefly, scheduling, distributed generation, optimization, power flow**

I. INTRODUCTION

A good electric power system must meet several requirements including reliability, quality, stability, and resilient. Monitoring, controlling, and planning fare needed to meet the power operation requirement. Moreover, it is necessary to adjust the generator side in providing power supply to the system in order to obtain efficiency in its operation with considering dynamic load. Scheduling generating units is a key issue on the power system operation [1] and needed to realize optimal power system operational conditions in terms of resources and costs [2].

An increasing load on the electric power system and decreasing non-renewable energy reserves have led to a growth in the use of renewable energy sources [3]. The potential for renewable energy is generally not too large and spread over a wide area. These conditions encourage the development of a distributed generation (DG) system to meet load requirements and increase system reliability [4]. The connection of DG tends to the power system more complex in its operation and control. Inappropriate generation unit scheduling causes higher power losses [5]. Scheduling problems can be modeled in mathematical programming to get the most appropriate generation settings from each generating unit [6].

In reference [7], the firefly algorithm (FA) sets the ON/OFF status and the lambda iterations determine the power generated by each generating unit. The firefly algorithm has better performance than the Integer Coded Genetic Algorithm ICGA [8], Shuffled Frog Leaping Algorithm (SFLA) [9], and Extended Priority List (EPL) [10]. This is indicated by the minimum cost when implemented in optimization of 10, 20, and 40 generating units. The hybrid method of priority list (PL) and modified firefly (M-FA) has been applied to solve the unit commitment problem. The first step is to determine the active generating unit based on PL. The second step, M-FA calculates the power of each active generator unit [11].

The firefly algorithm (FA) can be explained that the position of the individual firefly consists of the current position, movement towards a brighter firefly, and random movement. The random movement component has the potential to slow down the achievement of the final position according to the objective functions in the optimization.

This paper discusses the optimization of generating unit scheduling using the Adaptive Modified Firefly Algorithm (AMFA). This modification is an adjustment of the random movement components along with the iteration process to reduce the optimization process and calculation time simultaneously. AMFA's performance was tested by optimizing the generating unit scheduling of the modified IEEE 30-bus system. Load variations are 100%, 120%, and

130% of the baseload 242.55 MW. The performance parameter is the speed of convergence, generating cost, and power loss. In addition, how the DG installation affects the performance.

II. Mathematical Model

A. Thermal Generator Input-Output Equivalence

In meeting the power requirements of the load, a power system has n generators is required to determine the amount of generation for each generator. The power generation affects the fuel costs of each generating unit in the form of the input-output equivalence equation. An i-th generating unit has the fuel cost (F_i) as a function of the power generation (P_i) [12].

$$F_i(P_i) = a_i + b_i.P_i + c_i.(P_i\ )^2 \tag{1}$$

Where a_i, b_i, c_i are i-th input-output coefficients.

The total fuel cost (F_t) for the n generating units in the power system is the sum of the fuel costs for each generator in the system.

$$F_t = \sum_{i=1}^{n} F_i \tag{2}$$

B. Thermal Generator Constraint

There are several constraints in determining the power generation for a generating unit. The power requirements (P_D) in the system must be agreed with total power generation. This is the first constraint.

$$\sum_{i=1}^{n} P_i = P_D \tag{3}$$

As shown in Fig. 1, the generation of power determines the fuel costs and efficiency of the generating unit [3]. High efficiency occurs when the generation ranges between P_{min} and P_{max} which in that range has a low heat rate, as the second constraint. It can be formulated as below,

$$P_{i_{min}} \le P_i \le P_{i_{max}} \tag{4}$$

III. Optimization Algorithm

The firefly algorithm is a metaheuristic method developed by Xin Zhe Yang which is inspired by the behavior of fireflies based on 3 things [13]. First, fireflies are unisex. Second, the individual attraction is proportional to the brightness level. Fireflies have a higher brightness attract the less bright ones to move closer. When there is no difference in brightness, the movement is random. And thirdly, the value of the objective function affects the brightness.

A. AMFA

The AMFA algorithm is carried out by adapting the random movement components and applied to each iteration [14]. The attractiveness of firefly i to other firefly j depends on the brightness (β_O), the distance (r) and the light absorption coefficient (γ) between fireflies which is expressed by equation (5).

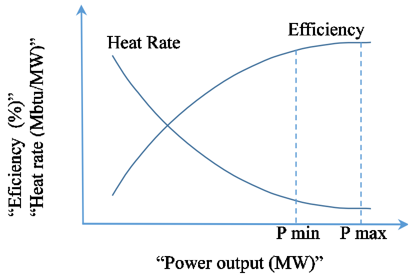

Fig. 1. Heat rate and Efficiency of Thermal Power Generation Unit

$$\beta = \beta_{0(Xj)}.e^{(-\gamma.r^m)} \quad , m \ge 1 \tag{5}$$

The Cartesian distance (r_{ij}) between fireflies i at positions X_i and j at X_j is expressed in equation (6).

$$r_{ij} = \left\| X_i - X_j \right\| = \sqrt{\sum_{m=1}^{k} \left(X_{j,m} - X_{i,m} \right)^2} \tag{6}$$

Where $X_{i,m}$ is the k-th component of the spatial coordinate X_i of the i-th firefly. For the 2-dimensional case, the distance equation can be written as below,

$$r_{ij} = \left\| X_i - X_j \right\| = \sqrt{\left(X_i - X_j \right)^2 + \left(Y_i - Y_j \right)^2} \tag{7}$$

The movement of the less bright firefly (X_i) towards the lighter firefly (X_j) is expressed as following equation,

$$X_i = X_i + \beta_0.e^{(-\gamma.r^m)}.(X_j - X_i) + \alpha.\varepsilon_i \tag{8}$$

where ε is a random value in a Gaussian distribution.

Based on equation (8), the movement of firefly has three components, namely the current position of the firefly (X_i), the movement towards a brighter firefly, and the random movement of a firefly with a range of (0,1).

The random movement component can cause the movement of the fireflies to be disorganized and make a slowdown in convergence. Moreover, it can be trapped in the local optima. Based on the previous statement, modifying the firefly algorithm is necessary to reduce the random movement component. The attenuation of the random movement is done by adjusting the value of the parameter α along with the iteration (k). Adaptive random movement can be expressed as following equation [14],

$$\alpha^{k+1} = \alpha^k.\left(\frac{1}{2} k_{max} \right)^{\frac{1}{k_{max}+1}} \tag{9}$$

B. Optimization of Generating Unit Scheduling

The electric power system must be able to adjust the power generation when load changes occur. It is done by adjusting the scheduling of the generating unit. Optimization of generating unit scheduling is to obtain optimal operation in the term of lowest generation cost. AMFA steps are shown in the pseudo-code of Fig. 2.

Read system data
Objective function f(p), p=(p₁,p₂,...,p_d)
Create an initial population of fireflies p_i (i=1,2,...n)
The light intensity I_i on p_i determine by $f(p_i)$
Setting a light absorption coefficient γ
Setting a randomize movement coefficient α
While (t<maximum iteration)
For i=1:n all n fireflies
For j=1:n all n fireflies
If (Ij>Ii), firefly i to j in d dimension; end if
Variation appeal to the distance r through exp[-γr]
Update value of alfa through reduction with U of each iteration
Evaluation of new solutions and update light intensity
End for j
End for i
Run power flow analysis using Newton Raphson
Calculate generation cost and power loss
Arrange fireflies and find the best currently
End while
Display the result of the process

Fig. 2. Pseudo Code

IV. MODIFIED IEEE 30-BUS POWER SYSTEM

To evaluate AMFA performance, a modified IEEE 30-bus system was used as the test system [15]. The system consists of 6 generating units as shown in Fig. 3. Units 1, 2, 5, and 6 are thermal, while units 3 and 4 are non-thermal generating units as DG. Table I describes the details of the load distribution at each bus. The system load data is 242.55 MW as the baseload. Table II describes the data of each generating unit in the system.

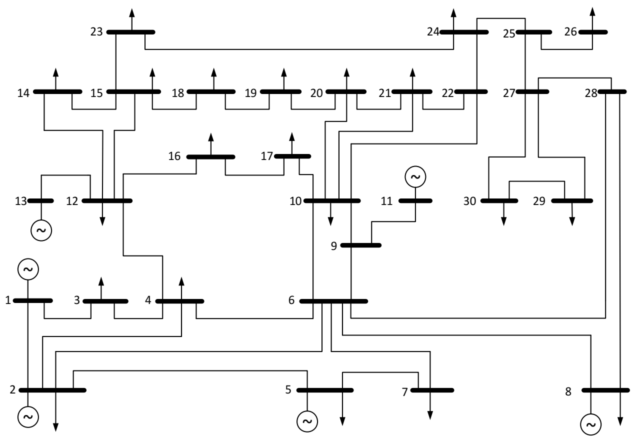

Fig. 3. IEEE 6 generator 30 bus systems

TABLE I. DISTRIBUTION OF LOAD ON EACH BUS FOR BASELOAD (242.55 MW AND 59.85 MVAR)

Bus	P_{Load} (MW)	Q_{Load} (MVAR)	Bus	P_{Load} (MW)	Q_{Load} (MVAR)
1	0.00	0.00	16	16.65	1.62
2	4.50	0.90	17	12.60	5.22
3	18.36	1.08	18	15.48	0.81
4	14.04	1.44	19	13.05	3.06
5	4.50	0.90	20	12.78	0.63
6	0.00	0.00	21	21.15	10.08
7	25.02	9.81	22	0.00	0.00
8	0.00	0.00	23	8.28	1.44
9	0.00	0.00	24	9.63	6.03
10	18.72	1.80	25	0.00	0.00
11	0.00	0.00	26	7.65	2.07
12	14.58	6.75	27	0.00	0.00
13	0.00	0.00	28	0.00	0.00
14	5.58	1.44	29	6.66	0.81
15	7.38	2.25	30	5.94	1.71

TABLE II. GENERATING UNIT DATA ON IEEE 30 BUS SYSTEM

Generating Unit	Bus	P_{min} (MW)	P_{max} (MW)	Input output coefficient		
				a	*b*	*c*
1	1	50	200	0	3.25	0.01834
2	2	50	150	0	3.00	0.03750
3	5	75	100	0	1.75	0.00000
4	8	10	35	0	1.75	0.00000
5	11	10	30	0	3.15	0.02500
6	13	50	100	0	3.10	0.02500

V. RESULT AND DISCUSSION

Optimization of generating units scheduling is performed with several loading conditions. Loading varieties include 100%, 120%, and 130% of the baseload. Optimization is carried out using the FA and AMFA methods and compared. Furthermore, the results are used as the value of power generation for each generating unit in power flow analysis using the Newton Raphson method.

A. Case-1: Optimization of 4 Generating Units

Case-1, the system load is 100%, 120%, and 130% of the baseload. The optimization process is limited to 2000 iterations. The number of a scheduled generating units is 4 units, where DG are not included. This simulation is intended to determine the performance of the FA and AMFA.

The optimization convergence of both methods is shown in Fig. 4. The simulation result provides that AMFA is faster than FA, and a number of iterations is 137 and 861, respectively. Moreover, time calculations are 13.08 and 84.59 seconds, respectively.

For the 3 types of loading, the performance comparison both of methods is presented in Table III. There was an improvement in the optimization process with AMFA compared to FA. Iteration and computation time are reduced significantly and simultaneously. The percentage of iteration reduction and calculation time reduction is obtained by comparing the reduction that occurs when using AMFA against FA.

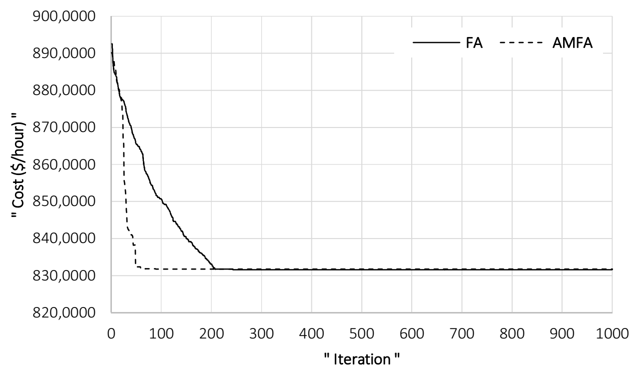

Fig. 4. Convergence of optimization process on scheduling for 4 generating units of IEEE 30-bus standard system with 100% baseload

TABLE III. PERFORMANCE COMPARISON OF FA AND AMFA FOR CASE-1

Load	Number of Iteration		% Iteration reduction	Calculation time (seconds)		% time reduction
	FA	*AMFA*		*FA*	*AMFA*	
100 %	861	137	84.09	84.59	13.08	84.54
120 %	177	79	55.37	17.11	7.62	55.46
130 %	229	126	44.98	22.27	12.22	45.13

TABLE IV. RESULT OF GENERATING UNITS SCHEDULING ON CASE-1, LOADING AT 100%, 120%, AND 130% OF BASELOAD.

Load	Para-meters	Methods	
		FA	*AMFA*
100% baseload	Total Load (MW)	242.5500	242.5500
	Total Gen (MW)	253.2195	253.2162
	Total Loss (MW)	10.6695	10.6662
	Gen 1 (MW)	60.6695	60.6662
	Gen 2 (MW)	50.0001	50.0000
	Gen 3 (MW)	92.5499	92.4963
	Gen 4 (MW)	-	-
	Gen 5 (MW)	-	-
	Gen 6 (MW)	50.0000	50.0537
	Tot Cost ($/hour)	887.8944	888.0830
	Gen 1 ($/hour)	264.6814	264.6635
	Gen 2 ($/hour)	243.7506	243.7500
	Gen 3 ($/hour)	161.9623	161.8685
	Gen 4 ($/hour)	-	-
	Gen 5 ($/hour)	-	-
	Gen 6 ($/hour)	217.5000	217.8010
120% baseload	Total Load (MW)	296.4500	296.4500
	Total Gen (MW)	314.3318	314.3218
	Total Loss (MW)	17.8818	17.8718
	Gen 1 (MW)	100.6279	100.4466
	Gen 2 (MW)	50.0000	50.0006
	Gen 3 (MW)	100.0000	100.0000
	Gen 4 (MW)	-	-
	Gen 5 (MW)	-	-
	Gen 6 (MW)	63.7039	63.8747
	Tot Cost ($/hour)	1230.4378	1230.2578
	Gen 1 ($/hour)	512.7512	511.4930
	Gen 2 ($/hour)	243.7500	243.7540
	Gen 3 ($/hour)	175.0000	175.0000
	Gen 4 ($/hour)	-	-
	Gen 5 ($/hour)	-	-
	Gen 6 ($/hour)	298.9366	300.0107
130% baseload	Total Load (MW)	323.4000	323.4000
	Total Gen (MW)	346.7438	346.7450
	Total Loss (MW)	23.3438	23.3450
	Gen 1 (MW)	121.0041	121.0221
	Gen 2 (MW)	51.0954	51.0981
	Gen 3 (MW)	100.0000	100.0000
	Gen 4 (MW)	-	-
	Gen 5 (MW)	-	-
	Gen 6 (MW)	74.6443	74.6249
	Tot Cost ($/hour)	1458.6780	1458.7020
	Gen 1 ($/hour)	661.7974	661.9359
	Gen 2 ($/hour)	251.1888	251.2071
	Gen 3 ($/hour)	175.0000	175.0000
	Gen 4 ($/hour)	-	-
	Gen 5 ($/hour)	-	-
	Gen 6 ($/hour)	370.6917	370.5590

The generation scheduling for case-1 is presented in Table IV. It is observed that AMFA is more optimal than FA with very small value differences. Improvements to the optimization of the objective function, which consists of total generation, total cost, and total loss, were not significant.

The results of the power flow analysis are listed in Table V. It shows that the bus voltage profile is the same for both FA and AMFA algorithms. This proves that the modifications made have been able to improve performance while maintaining accuracy. It is observed that bus voltage less than IEEE standard 141-1986 using both methods are 1, 18, and 20 buses for 100%, 120%, and 130% of based load, respectively. The voltage profile tends to be worse when the load increased. This condition is improved by DG in case-2.

TABLE V. RESULTS OF POWER FLOW ANALYSIS ON CASE-1 USING FA AND AMFA, LOADING AT 100%, 120%, AND 130 % OF THE BASELOAD

Bus	|V| (p.u)					
	100 % baseload		*120 % baseload*		*130 % baseload*	
	FA	*AMFA*	*FA*	*AMFA*	*FA*	*AMFA*
1	1.0500	1.0500	1.0500	1.0500	1.0500	1.0500
2	1.0450	1.0450	1.0329	1.0329	1.0254	1.0254
3	1.0029	1.0029	0.9747	0.9747	0.9571	0.9571
4	0.9945	0.9946	0.9610	0.9611	0.9402	0.9402
5	1.0173	1.0173	1.0100	1.0100	1.0100	1.0100
6	0.9828	0.9829	0.9456	0.9456	0.9226	0.9226
7	0.9850	0.9850	0.9572	0.9573	0.9424	0.9424
8	0.9821	0.9821	0.9441	0.9442	0.9206	0.9206
9	0.9488	0.9488	0.8892	0.8892	0.8492	0.8492
10	0.9345	0.9345	0.8660	0.8661	0.8193	0.8193
11	0.9488	0.9488	0.8892	0.8892	0.8492	0.8492
12	0.9901	0.9902	0.9303	0.9304	0.8888	0.8888
13	1.0365	1.0365	0.9774	0.9775	0.9357	0.9357
14	0.9675	0.9675	0.9009	0.9009	0.8548	0.8548
15	0.9501	0.9502	0.8785	0.8786	0.8289	0.8288
16	0.9503	0.9503	0.8811	0.8811	0.8334	0.8334
17	0.9328	0.9328	0.8619	0.8619	0.8134	0.8134
18	0.9154	0.9154	0.8340	0.8341	0.7778	0.7778
19	0.9075	0.9075	0.8252	0.8252	0.7686	0.7686
20	0.9105	0.9105	0.8302	0.8303	0.7751	0.7751
21	0.9212	0.9213	0.8481	0.8481	0.7983	0.7983
22	0.9222	0.9222	0.8493	0.8493	0.7997	0.7997
23	0.9276	0.9276	0.8514	0.8515	0.7991	0.7990
24	0.9139	0.9139	0.8373	0.8373	0.7851	0.7851
25	0.9236	0.9236	0.8535	0.8535	0.8060	0.8060
26	0.8926	0.8926	0.8116	0.8116	0.7568	0.7568
27	0.9443	0.9443	0.8837	0.8838	0.8430	0.8430
28	0.9755	0.9755	0.9343	0.9343	0.9084	0.9084
29	0.9208	0.9208	0.8524	0.8524	0.8066	0.8066
30	0.9169	0.9170	0.8473	0.8473	0.8007	0.8007

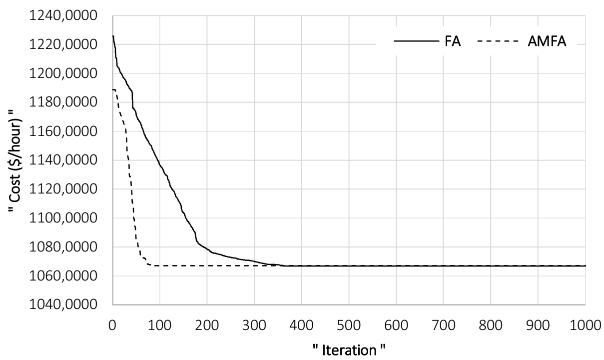

Fig. 5. Convergence of optimization process on scheduling for 6 generating units of IEEE 30-bus standard system with 130% baseload

B. Case-2: Optimization of 6 Generating Units

Case-2, the number of a scheduled generating units is 6 units, where DG are included. The system load is 100%, 120%, and 130% of baseload. The optimization process is limited to 1000 iterations. This simulation is to examine the performance of the proposed AMFA method for optimizing the scheduling of 6 generating units. In addition, DG's ability to improve the results of generating unit scheduling and bus voltages against increased loads is also analyzed.

Based on the results shown in Fig. 5, AMFA is faster than FA, and the number of iterations is 501 and 1685, respectively for 100% based load, while the calculation time is 93.0789 and 318.8468 seconds, respectively.

TABLE VI. PERFORMANCE COMPARISON OF FA AND AMFA FOR CASE-2

Load	Number of Iteration		% Iteration reduction	Calculation time (seconds)		% time reduction
	FA	*AMFA*		*FA*	*AMFA*	
100 %	1685	501	70.27	318.85	93.08	70.81
120 %	531	107	79.85	56.18	11.04	80.35
130 %	524	89	83.02	58.63	9.31	84.13

For the 3 types of loading, the performance comparison both of methods is presented in Table VI. With AMFA, the iteration decreases between 70.27% - 83.02%, while the calculation time decreases by 70.81% - 84.13%.

Table VII presents a comparison of the optimization results for case-1 and case-2. In case-2, the optimization involves 6 generating units consisting of 4 thermal units and 2 DG units as previously described.

TABLE VII. GENERATING UNITS SCHEDULING ON CASE-1 AND CASE-2, LOADING AT 100%, 120%, AND 130% OF BASELOAD

Load	Para-meters	AMFA Methode	
		Case-1	*Case-2*
100% baseload	Total Load (MW)	242.5500	242.5500
	Total Gen (MW)	253.2162	250.6112
	Total Loss (MW)	10.6662	8.0612
	Gen 1 (MW)	60.6662	55.6112
	Gen 2 (MW)	50.0000	50.0000
	Gen 3 (MW)	92.4963	75.0000
	Gen 4 (MW)	-	10.0000
	Gen 5 (MW)	-	10.0000
	Gen 6 (MW)	50.0537	50.0000
	Tot Cost ($/hour)	888.0830	881.4549
	Gen 1 ($/hour)	264.6635	237.4549
	Gen 2 ($/hour)	243.7500	243.7500
	Gen 3 ($/hour)	161.8685	131.2500
	Gen 4 ($/hour)	-	17.5000
	Gen 5 ($/hour)	-	34.0000
	Gen 6 ($/hour)	217.8010	217.5000
120% baseload	Total Load (MW)	296.4500	296.4500
	Total Gen (MW)	314.3218	308.3770
	Total Loss (MW)	17.8718	11.9270
	Gen 1 (MW)	100.4466	61.9270
	Gen 2 (MW)	50.0006	50.0000
	Gen 3 (MW)	100.0000	100.0000
	Gen 4 (MW)	-	35.0000
	Gen 5 (MW)	-	11.4500
	Gen 6 (MW)	63.8747	50.0000
	Tot Cost ($/hour)	1230.2578	1008.4390
	Gen 1 ($/hour)	511.4930	271.5940
	Gen 2 ($/hour)	243.7540	243.7500
	Gen 3 ($/hour)	175.0000	175.0000
	Gen 4 ($/hour)	-	61.2500
	Gen 5 ($/hour)	-	39.3450
	Gen 6 ($/hour)	300.0107	217.5000
130% baseload	Total Load (MW)	323.4000	323.4000
	Total Gen (MW)	346.7450	336.9210
	Total Loss (MW)	23.3450	13.5210
	Gen 1 (MW)	121.0221	71.9210
	Gen 2 (MW)	51.0981	50.0000
	Gen 3 (MW)	100.0000	100.0000
	Gen 4 (MW)	-	35.0000
	Gen 5 (MW)	-	30.0000
	Gen 6 (MW)	74.6249	50.0000
	Tot Cost ($/hour)	1458.7020	1143.1110
	Gen 1 ($/hour)	661.9359	328.6110
	Gen 2 ($/hour)	251.2071	243.7500
	Gen 3 ($/hour)	175.0000	175.0000
	Gen 4 ($/hour)	-	61.2500
	Gen 5 ($/hour)	-	117.0000
	Gen 6 ($/hour)	370.5590	217.5000

TABLE VIII. RESULTS OF POWER FLOW ANALYSIS ON CASE-1 AND CASE-2 USING AMFA, LOADING AT 100%, 120%, AND 130 % OF THE BASELOAD

Bus	|V| (p.u.)					
	100 % baseload		***120 % baseload***		***130 % baseload***	
	Case-1	***Case-2***	***Case-1***	***Case-2***	***Case-1***	***Case-2***
1	1.0500	1.0500	1.0500	1.0500	1.0500	1.0500
2	1.0450	1.0450	1.0329	1.0450	1.0254	1.0450
3	1.0029	1.0178	0.9747	1.0108	0.9571	1.0067
4	0.9946	1.0125	0.9611	1.0046	0.9402	1.0000
5	1.0173	1.0254	1.0100	1.0256	1.0100	1.0230
6	0.9829	1.0067	0.9456	1.0002	0.9226	0.9968
7	0.9850	1.0033	0.9573	0.9965	0.9424	0.9924
8	0.9821	1.0100	0.9442	1.0100	0.9206	1.0100
9	0.9488	1.0022	0.8892	0.9898	0.8492	0.9775
10	0.9345	0.9777	0.8661	0.9585	0.8193	0.9436
11	0.9488	1.0500	0.8892	1.0491	0.8492	1.0359
12	0.9902	1.0128	0.9304	0.9987	0.8888	0.9837
13	1.0365	1.0500	0.9775	1.0447	0.9357	1.0302
14	0.9675	0.9929	0.9009	0.9739	0.8548	0.9564
15	0.9502	0.9784	0.8786	0.9564	0.8288	0.9378
16	0.9503	0.9822	0.8811	0.9622	0.8334	0.9453
17	0.9328	0.9728	0.8619	0.9519	0.8134	0.9355
18	0.9154	0.9502	0.8341	0.9216	0.7778	0.8999
19	0.9075	0.9455	0.8252	0.9163	0.7686	0.8947
20	0.9105	0.9500	0.8303	0.9222	0.7751	0.9016
21	0.9213	0.9638	0.8481	0.9410	0.7983	0.9240
22	0.9222	0.9643	0.8493	0.9417	0.7997	0.9247
23	0.9276	0.9600	0.8515	0.9344	0.7990	0.9145
24	0.9139	0.9513	0.8373	0.9248	0.7851	0.9054
25	0.9236	0.9570	0.8535	0.9334	0.8060	0.9167
26	0.8926	0.9271	0.8116	0.8956	0.7568	0.8743
27	0.9443	0.9746	0.8838	0.9569	0.8430	0.9441
28	0.9755	1.0011	0.9343	0.9936	0.9084	0.9894
29	0.9208	0.9518	0.8524	0.9283	0.8066	0.9122
30	0.9170	0.9481	0.8473	0.9236	0.8007	0.9070

TABLE IX. THE NUMBER OF BUSES EXPERIENCING LOW VOLTAGE (<0.9 P.U.) ON CASE-1 AND CASE-2, LOADING AT 100%, 120%, AND 130 % OF THE BASELOAD

Loading	Number of Low Voltage Bus	
	Case-1	***Case-2***
100% Based Load	1 bus	0 bus
120% Based Load	18 bus	1 bus
130% Based Load	21 bus	3 bus

The optimization results show a smaller of total generation, total cost and total power loss. Thus the operation of the system is more optimal. This proves DG's ability to improve the optimization results.

The power flow analysis based on the scheduling results in Table VII has provided a bus voltage profile. Table VIII presents a comparison of the bus voltage profiles in *case-1* and *case-2* for 3 types of loading. In *case-2*, the bus voltage profile is much better than in *case-1*. The number of buses experiencing low voltage is significantly reduced. Table IX summarizes the number of bus voltages below 0.9 p.u for both test cases.

VI. CONCLUSION

The adaptive modified firefly (AMFA) algorithm by reducing the random movement components of firefly has improved its performance. There is an improvement in the speed of convergence significantly. Increasing the speed of the optimization process opens up opportunities for online optimization implementation when the power system is operating. The involvement of DG able to improve profile bus voltage. Moreover, DG can also improve optimal conditions in terms of total generation, generation cost, and power losses. This will be advantageous in the planning of short-term power system operations against daily load changes. In future work, it is necessary to study the application of the AMFA algorithm for optimization of unit commitments in real power systems where the generating unit has more complicated input-output characteristics.

ACKNOWLEDGMENT

The author would like to thank the Ministry of Education and Culture for providing research funding support through the PDUPT research grant.

REFERENCES

[1] I. Abdou and M. Tkiouat, "Unit commitment problem in electrical power system: A literature review," *Int. J. Electr. Comput. Eng.*, vol. 8, no. 3, pp. 1357–1372, 2018.

[2] S. Y. Abujarad, M. W. Mustafa, and J. J. Jamian, "Recent approaches of unit commitment in the presence of intermittent renewable energy resources: A review," *Renew. Sustain. Energy Rev.*, vol. 70, no. October 2015, pp. 215–223, 2017.

[3] Allen J. Wood, Bruce F Wollenberg, and Gerald B. Sheble, *Power Generation, Operation, and Control*, Third. John Willey, 2014.

[4] R. S. Wibowo, K. R. Firmansyah, N. K. Aryani, and A. Soeprijanto, "Dynamic economic dispatch of hybrid microgrid with energy storage using quadratic programming," *IEEE Reg. 10 Annu. Int. Conf. Proceedings/TENCON*, no. 3, pp. 667–670, 2017.

[5] B. Banhthasit, C. Jamroen, and S. Dechanupaprittha, "Optimal Generation Scheduling of Power System for Maximum Renewable Energy Harvesting and Power Losses Minimization," vol. 8, no. 4, pp. 1954–1966, 2018.

[6] L. Yang, C. Zhang, J. Jian, K. Meng, Y. Xu, and Z. Dong, "A novel projected two-binary-variable formulation for unit commitment in power systems," *Appl. Energy*, vol. 187, pp. 732–745, 2017.

[7] Manabjyoti Daimari and Dr. Barnali Goswami, "Firefly based Unit Commitment," *Int. J. Eng. Res.*, vol. V5, no. 12, pp. 221–225, 2016.

[8] I. G. Damousis, A. G. Bakirtzis, and P. S. Dokopoulos, "A solution to the unit-commitment problem using integer-coded genetic algorithm," *IEEE Trans. Power Syst.*, vol. 19, no. 2, pp. 1165–1172, 2004.

[9] K. Selvakumar, T. Venkatesan, and M. Y. Sanavullah, "Price based unit commitment problem solution using shuffled frog leaping algorithm," *IEEE-International Conf. Adv. Eng. Sci. Manag. ICAESM-2012*, vol. 26, no. 2, pp. 794–799, 2012.

[10] T. Senjyu, K. Shimabukuro, K. Uezato, and T. Funabashi, "A fast technique for unit commitment problem by extended priority list," *IEEE Trans. Power Syst.*, vol. 18, no. 2, pp. 882–888, 2003.

[11] B. M. Hussein and A. S. Jaber, "Unit commitment based on modified firefly algorithm," *Meas. Control*, vol. 53, no. 3–4, pp. 320–327, 2020.

[12] B. K. Panigrahi and V. Ravikumar Pandi, "Bacterial foraging optimisation: Nelder-Mead hybrid algorithm for economic load dispatch," *IET Gener. Transm. Distrib.*, vol. 2, no. 4, pp. 556–565, 2008.

[13] Xin-SheYang, *Engineering Optimization : An Introduction with Metaheuristic Applications*. John Willey, 2010.

[14] A. Tjahjono, D. O. Anggriawan, A. K. Faizin, A. Priyadi, M. Pujiantara, and M. H. Purnomo, "Adaptive modified firefly algorithm for optimal coordination of overcurrent relays," pp. 2575–2585, 2017.

[15] A. Priyadi *et al.*, "Transient stability assessment as boundary value problem," *2008 IEEE Electr. Power Energy Conf. - Energy Innov.*, pp. 1–6, 2008.