ISSN 2347 - 3983
Volume 8. No. 1.1, 2020
International Journal of Emerging Trends in Engineering Research
Available Online at http://www.warse.org/IJETER/static/pdf/file/ijeter2581.12020.pdf
https://doi.org/10.30534/ijeter/2020/2581.12020

Solving Non-Smooth Economic Load Dispatch Problem via Flower Pollination Algorithm

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ABSTRACT

This paper discusses the generator optimization method for non-smooth economic dispatch (ED) in power systems using the Flower Pollination Algorithm (FPA). The generating value of each unit is determined without compromising the power limits of each generator and the amount of energy demand. The objective of this study is to provide the minimumgenerating costs based on the seamless cost function of the ED. The feasibility of the FPA method is compared with particle swarm optimization (PSO) and moth flame optimizer (MFO). Two types of power system networks, 10- and 40-generators, are tested using MATLAB. Simulation results show that compared with PSO and MFO,FPA provides better results in optimizing energy generation with minimum generation cost and power loss.

Key words: non-smooth economic dispatch, flower pollination algorithm, moth flame optimizer, particle swarm optimization

1. INTRODUCTION

Today, fuel savings are a priority in the world power generation sector. The scarcity of new oil sources, coupled with populationincrease, has led to rising fuel prices. Without sacrificing energy demand, power generation strategies with minimal oil costs are highlyessential. Suchscheduling strategiescan be based on economic dispatch (ED) calculations.

ED schedules the power unit operations to meet a specific power demand while also imposing a minimum fuel cost. Categorized as atype of optimization problem, ED solutions using optimization can be divided into mathematical and heuristic techniques. Mathematical techniques include linear [1-2], quadratic [3], and mixed integer [4]programming. These traditional ED solutionsare time consuming, cannot solve non-linear cost functions, and provide suboptimalsolutions. The above disadvantages have ledscientists to introduce heuristic approaches. ED problems can be categorized assmooth and non-smooth. In non-smooth problems, the impact of the valve system is considered in the power generation cost function. Both smooth and non-smooth problems aresuccessfully solved using heuristic techniques as reported, respectively, in [5-6] and [7-10].

Artificial intelligence (AI) is widely used in the field of power systems. Among the techniques used are evolutionary programming (EP) [11-14], particle swarm optimization (PSO) [15-18], moth flame optimization (MFO) [19-22], and whale optimization algorithm (WOA) [23-25]. EP is developed on the basis of biological evolution. A key feature of the EP is the mutation, in which each parent produces a new breed with different characteristics. Selection is based on the fittest generation. By comparison, the PSO technique mimics the behavior of a herd of animals or insects. During the search, two types of exploration,global and local, are carried out. Balance between these two explorations is the key to obtain the optimal solution. Meanwhile, MFO was developed on the basis of flying moths, called transverse orientation. At night, flying moths are guided by moonlight and maintain a constant angle to find their way. In the presentstudy, a new metaheuristic-based method called Flower Pollination Algorithm (FPA) is introduced. FPAisdeveloped based on pollen transfer from one flower to another using honeybees, birds, water, or wind. Among the advantages of FPA over other techniques is the simplicity and speed of the search. Its optimization capabilities are proven and used in various optimization problems such as economics delivery, engineering design, and medical applications [26-30].

This study proposes efficient techniques for calculating optimal non-smooth power generation capacity based on power demand and the constraints of each generator unit using FPA optimization technique. Test systems using 10- and 40-unit power generatorsaresimulated using MATLAB. The objective function of this optimization is to minimize the total cost of power generation. To determine the performance of the proposed technique, the FPAtechniqueisalso compared withthe PSO and MFO.

The rest of the paper is organized as follows.Section 2 presents the ED problem formulation. Section 3 explainsthe MFO algorithm. Section 4 discussesthe implementation of optimal power-scheduling algorithm. Section 5 providesthe simulation results and discussions. Lastly, Section 6 presents the conclusions.

2. ED PROBLEM FORMULATION

ED is an issue for determining the power capacity that each unitin the power system must generate to minimize the cost. At the same time, the amount of generated power should meet specific power demand and within the specified rangefor each generator.ED has two categories of problem formulations: smooth and non-smooth cost functions.

2.1 ED Problem with Smooth Cost Functions

For ED problems with smooth cost function, the cost function of each generator is represented by the quadratic function as follows,

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

Here, P_i is the real power output of the i^{th}generator, in MW. $C(P_i)$ is the production cost of P_i, in RM per hour. While, a_i, b_i, and c_i are threegeneration cost coefficients ofP_i. The total production cost C_T of one power system network can be expressed as

$$C_T = C(P_1) + C(P_2) + \cdots\cdots + C(P_n) = \sum_{i=1}^{n} C(P_i) . \quad (2)$$

Here, n is number of the generating units in the system.

2.2 ED Problem with Non-Smooth Cost Functions

In reality, using quadratic functions alone to estimate the cost of production per generator unit is inappropriate. The reason is the multiple valve system per generator unit, which considerablyaffects the cost function of each generator unit.To consider the effect of this valve system, the generation cost function is restructured by integrating with sinusoidal functions, as follows

$$C(P_i) = a_i + b_i P_i + c_i P_i^2 + \left| e_i sin\left(f_i\left(P_i^{min} - P_i\right)\right)\right| . \quad (3)$$

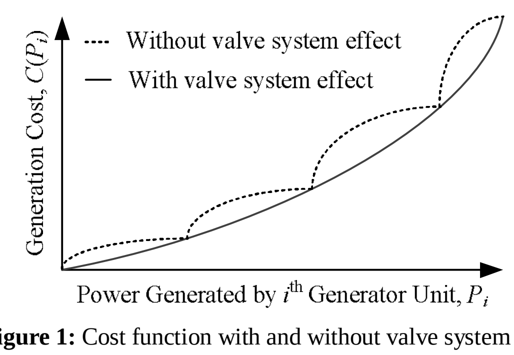

Figure 1: Cost function with and without valve system effect

Here, same asa_i, b_i, and c_i, e_i and f_i are also generation cost coefficients of P_i.Figure 1 illustrates the valve system effect on cost function. The pattern with the valve system effect is ascending and decreasing along the quadratic line.

2.3 Constraints

Basically, constraints that need to be considered in ED are operating limits for each generator unit and power demand. The operating limits of one generator unit is unique compared withthe others and can be written as

$$P_i^{min} \leq P_i \leq P_i^{max} . \quad (4)$$

Here, P_i^{min} and P_i^{max} are the minimum and maximum operating limits of P_i, respectively.In addition, the total amount of power generated by all units must be the same or largerthan the total power demand. In this study, the total amount of power generated orP_G can be expressed as

$$P_G = \sum_{i=1}^{n} P_i = P_D + P_L . \quad (5)$$

Here, P_D is the total power demand andP_L is the total power loss. One of the criteria of a good generation system is theproduction of a low amount of P_L.

3. FLOWER POLLINATION ALGORITHM

3.1 Concept of Flower Pollination Algorithm

Basically, flower pollination is the process of transferring pollen from one flower to another, using pollinators (biotic) such as honeybees and birds or no pollinator (abiotic), where pollen is dispersed by water or wind.In addition to biotic and abiotic, pollination can be divided into two, namely,self-pollination or cross-pollination. The former is a pollination of the same type of crop, whilethe latter (allogamy) is the pollination of two different crop types.

3.2 Flower Pollination Algorithm Optimization Technique

Xin-She Yang introduced flower pollination algorithm (FPA) optimization technique in 2012. Yang has developed FP techniques based on the goals for achieving optimum pollination in terms of the quantity and quality of flowers produced. Based on the natural flower pollination, abiotic and self-pollination is considered as local pollination. Meanwhile, biotic and cross-pollination are produced by pollinators capable of flying long distances such asbees, birds, and flies. This processcan be considered as a global pollination. To produce the bee and bird flight patterns, Lévy Flight can be adopted, given thatthe flight steps of these animals comply with the Lévy distribution values. The natural selection of global or local pollination is a random process. However, due to the close proximity of pollination and other factors such as wind and water, the majority of pollination islocal.

In summary, the FPA technique complies with four conditions, as illustrated in Table 1.

Table 1: Four conditions in FPA

Conditions	Details
Condition 1	Cross and biotic pollination are considered as global pollination. Pollinators carrying pollen are moving on Lévy flights.
Condition 2	Self and abiotic pollination are considered as local pollination.
Condition 3	Reproduction probability of flowers is considered as proportional to the similarity of two involved flowers.
Condition 4	Local and global pollination are determined by probability (range from 0 until 1). Due to the close proximity of pollination and other factors such as wind and water, most pollination activities are local.

Global pollination as Condition 1 can be represented mathematically as:

$$x_i^{t+1} = x_i^t + L(x_i^t - x_{best}). \qquad (6)$$

Here, x_i^t is the i^{th}pollen at iteration t,x_{best} is the best current pollen (solution) among all pollens until iteration t, and$L$ is a step size of pollination. Insects and birds can travel long distances and at various distance steps. Lévy Flight caneffectively replicate this feature well. Based on Levy distribution, approximation of L is as follows,

$$L \sim \left(\lambda\Gamma(\lambda)sin(0.5\pi\lambda)\right)/\pi s^{1+\lambda} > 0 \quad (s \gg s_0 > 0). \qquad (7)$$

Here, $\Gamma(\lambda)$ is the standard gamma function. This distribution is valid for large steps, s > 0. The value of λ is 1.5.

As Condition 2, local pollination can be represented mathematically as

$$x_i^{t+1} = x_i^t + \beta\left(x_j^t - x_k^t\right). \qquad (8)$$

Here, x_j^t and x_k^t are both pollens from different flowers of the same plant species andβ is a uniform distributionwith value from 0 until 1.

According to Condition 4, pollination occurs globally or locally. With $p$as a boundary value, global pollination is carried outif the random value exceeds p. Otherwise, local pollination is carried out. In this study, the p is defined as 0.8.

The stopping criteria for all three techniques are:
(i.) The difference between the maximum and minimum F_{all} is less than 0.1% of minimum F_{all}
(ii.) The current iteration is equal to the maximum number of iterations NI_{max}

Figure 2 shows the FPA optimization technique summarized in the form of a flow chart.

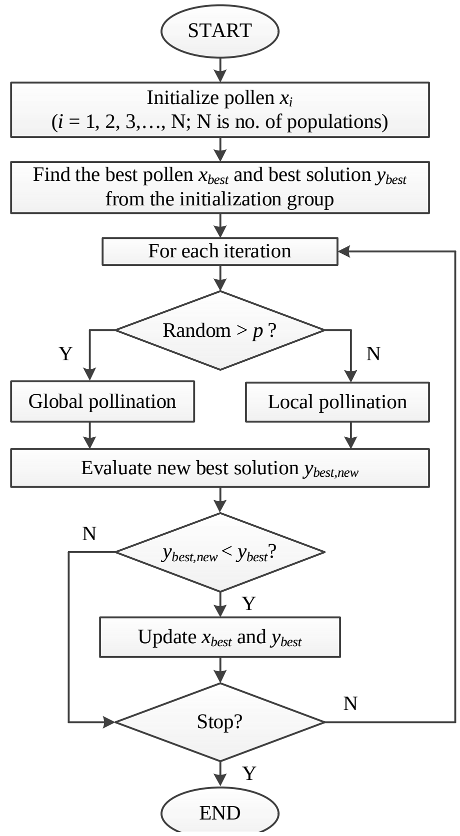

Figure 2: Flow chart of FPA optimization technique

4. OPTIMAL POWER-SCHEDULING ALGORITHM

In this study, simulations are carried outin MATLAB environment. Two test systems are involved: 10generators and 40generators systems, with non-smooth fuel cost function [9]. Events 1-A and 1-B areconducted using 10generators test system, while Events 2-A and 2-B arecarried outusing a 40-generator test system. Figure 3 shows the flowchart for P_{all} and F_{all} calculations. The criteria for termination of this computation are the same as those mentioned in Subsection 3.2.

At each event, a total of 100 cases are simulated to obtain the optimum results for each technique. The maximum number of iterations for each case is 500. The objective function of these simulations is to minimize power generation cost F_{all}. On the basis of 100 cases, an analysis of the consistency of the results obtained can be made. Table 2 illustrates all the events with specific power demand.

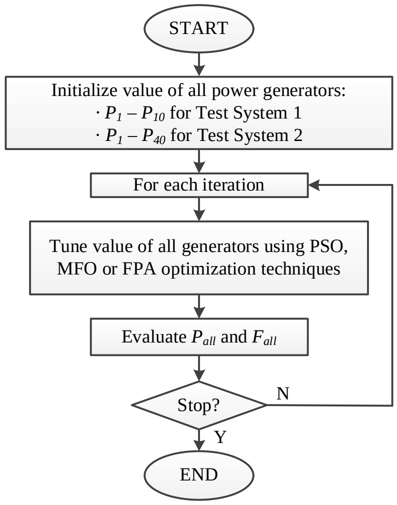

Figure 3: Flow chart for P_{all} and F_{all} calculations

Table 2: List of test systems, events, and power demand

No.	Test System	Event	Power Demand
1	Ten generators system	Event 1-A	1500 MW
		Event 1-B	2100 MW
2	Forty generators system	Event 2-A	8100 MW
		Event 2-B	10100 MW

The characteristics of ten and forty generators system, which consists of fuel cost coefficients (a_i, b_i, c_i, d_i, and e_i) with minimum and maximum power limits (P_{min} and P_{max}) for each generator unit can be found in Appendix.

For each event, three optimization techniques: PSO, MFO, and FPA are used to tune all unit generators in the test systems. Each technique has specific parameters to control the accuracy and speed of the optimization. Table 3 lists the parameter values for PSO, MFO, and FPA.

Table 3: List of PSO, MFO, and FPA parameters

Method	Parameters
PSO [16]	$c_1 = c_2 = 0.5, \omega = 0.05$
MFO [21]	$t \in (-1,1), b = 0.05$
FPA	$\lambda = 1.5, p = 0.8, \beta \in (0,1)$

5. RESULTS AND DISCUSSION

The result of best generation values for all 10 generators (P_{G1}–P_{G10}) with minimum total power generation costs F_{all} using PSO, MFO, and FPA for Event 1-A are summarized in Table 4. From the results, FPA produces the least value of F_{all}, followed by PSO and MFO. This shows that FPA can provide the best cost savings compared with the other two techniques. Table 4shows that the total generated power P_{all} for FPA and MFO are larger than the power demand, P_D. Despite the loss of power, these values are considered small, not more than 0.1% of P_D.

Table 4: Best Power Scheduling with Minimum Cost Generation for Event 1-A (P_D = 1500 MW)

P* and *F	**Optimization Techniques**		
	PSO	**MFO**	**FPA**
P_{G1} (MW)	31.375	39.640	38.201
P_{G2} (MW)	51.463	35.155	44.964
P_{G3} (MW)	64.884	90.642	74.552
P_{G4} (MW)	48.730	83.019	45.617
P_{G5} (MW)	63.786	65.359	53.395
P_{G6}(MW)	70.558	70.000	72.277
P_{G7} (MW)	195.219	205.310	200.617
P_{G8} (MW)	197.897	270.996	237.529
P_{G9} (MW)	338.907	350.701	371.307
P_{G10}(MW)	437.180	290.095	362.162
P_{all} (MW)	1500.000	1500.917	1500.674
F_{all}(RM)	78848.40	79353.89	78778.52

Table 5 shows the best, worst, and average values for P_{all}, F_{all} and number of iterations, *NI* calculated using PSO, MFO, and FPA techniques for Event 1-A. These best, worst, and average results are obtained from 100 simulated cases in Event 1-A. This result only looks at the value of one criterion, be it P_{all}, F_{all}, or *NI*. On this basis, the best, worst, and average values for F_{all} obtained by all three techniques are nearly identical. Similarly, in the P_{all} results, the PSO, MFO, and FPA methods provide average values of power loss P_L less than 0.2% P_D. This result shows that all three methods can effectively schedule low-cost energy generation while providing sufficient energy for the required power demand.

Table 5: Best, Worst,& Average Values of Power Scheduling, Generation Cost, and No. of Iterations for Event 1-A

F_{all}, P_{all}, and *NI*		**Optimization Techniques**		
		PSO	**MFO**	**FPA**
F_{all} (RM)	Best	78848.40	79353.89	78778.52
	Worst	79870.79	80297.21	79916.76
	Average	79360.54	79735.98	79431.26
P_{all} (MW)	Best	1500.000	1500.000	1500.000
	Worst	1500.887	1508.559	1514.844
	Average	1500.028	1500.985	1502.655
NI	Best	64	68	17
	Worst	500	252	60
	Average	168.51	119.3	33.11

In terms of *NI*, FPA calculates the smallest number of iterations compared with the PSO and MFO techniques. FPA has a total range of 17–60 iterations while the average *NI* is 33.11 iterations. By contrast, calculations using the PSO method require at least 64 iterations to produce results. Simulations using PSO do not converge until the calculation reaches a maximum of 500 iterations. On the basis of these *NI* results for Event 1-A, the FPA is capable of producing computations in a shorter time than the other two techniques. PSO, on the other hand, is the most time-consuming,taking longer than the specified number of iterations to complete. With F_{all} and P_{all} results similar to PSO and MFO, the lowest *NI* values show that FPA is the most efficient technique.

Table 6 summarizes the results of the best generation values for P_{G1}–P_{G10} with minimum F_{all} using all three techniques for Event 1-B. P_{all} calculated using all three techniques results in a very small power loss of 0.001% P_D. In terms of F_{all}, the FPA remains ahead of PSO and MFO in producing the lowest power generation cost.

Table 6: Best Power Scheduling with Minimum Generation Cost for Event 1-B (P_D = 2100 MW)

P and F	Optimization Techniques		
	PSO	MFO	FPA
P_{G1} (MW)	36.222	33.324	43.111
P_{G2} (MW)	76.519	79.984	78.244
P_{G3} (MW)	96.230	95.290	103.715
P_{G4} (MW)	95.449	129.994	128.735
P_{G5} (MW)	99.687	115.397	83.809
P_{G6}(MW)	184.154	152.277	117.504
P_{G7} (MW)	265.855	247.218	275.535
P_{G8} (MW)	339.365	337.618	330.133
P_{G9} (MW)	467.141	468.911	469.317
P_{G10}(MW)	439.378	439.986	469.919
P_{all} (MW)	2100.000	2100.000	2100.023
F_{all}(RM)	114188.58	113991.34	112857.42

Table 7 tabulates the best, worst, and average values for P_{all}, F_{all}, and *NI* calculated using all three optimization techniques for Event 1-B. FPA provides less F_{all} for best, worst, and average values, compared with PSO and MFO. In terms of P_{all}, the results produced by all three optimization methods provideP_L less than 0.2% P_D. In terms of*NI*, FPA can solve computational simulations faster compared with PSO and MFO. Moreover, the average *NI* for PSO can reach 105 iterations. Thus, FPA remains at the forefront of producing the lowest power generation cost at minimum power loss and minimum number of iterations compared with PSO and MFO techniques.

Table 7: Best, Worst,& Average Value of Power Scheduling, Generation Cost, and No. of Iterations for Event 1-B

P_{all}, P_{all}, and *NI*		Optimization Techniques		
		PSO	MFO	FPA
F_{all} (RM)	Best	114188.58	113991.34	112857.42
	Worst	114603.76	114597.51	114590.12
	Average	114536.59	114428.28	114298.85
P_{all} (MW)	Best	2100.000	2100.000	2100.000
	Worst	2100.089	2100.880	2104.205
	Average	2100.001	2100.053	2100.307
NI	Best	57	15	4
	Worst	278	54	43
	Average	105.98	27.96	12.98

In Events 2-A and 2-B, the test system consists of 40 generators simulated to calculate the result of best generation values (P_{G1}–P_{G40}) with minimum F_{all}. Table 8 shows the best, worst, and average values for P_{all}, F_{all}, and *NI* calculated using PSO, MFO, and FPA techniques for Event 2-A.

Table 8: Best, Worst,& Average Value of Power Scheduling, Generation Cost, and No. of Iterations for Event 2-A

P_{all}, P_{all}, and *NI*		Optimization Techniques		
		PSO	MFO	FPA
F_{all} (RM)	Best	100982.99	101309.67	9983.08
	Worst	103333.27	105096.06	103857.28
	Average	102411.44	103170.20	102179.09
P_{all} (MW)	Best	8100.012	8100.032	8100.323
	Worst	8105.705	8102.939	8103.387
	Average	8100.698	8100.505	8100.586
NI	Best	24	50	11
	Worst	500	500	133
	Average	186.64	236.41	31.43

F_{all} values calculated using the FPA method are the cheapest compared with MFO and PSO. The best, worst, and average F_{all} optimized by FPA are RM9983.08, RM103857.28, and RM102179.09, respectively. On the other hand, P_{all} calculated by all optimization techniques are almost the same value with P_D. PSO records the highest average of P_L, which is 0.009% of P_D and can be considered within the acceptable range. In terms of NI, FPA still provides the smallest iterations compared with the other two techniques, with an average *NI*of 31.43 iterations. From the results, at least one case for both PSO and MFO does not converge until 500 iterations are reached.

Table 9: Best, Worst,& Average Value of Power Scheduling, Generation Cost, and No. of Iterations for Event 2-B

P_{all}, P_{all}, and *NI*		Optimization Techniques		
		PSO	MFO	FPA
F_{all} (RM)	Best	127915.25	129225.41	124904.96
	Worst	129085.35	131398.47	128937.78
	Average	128410.55	130409.15	127946.19
P_{all} (MW)	Best	10100.019	10100.001	10100.072
	Worst	10104.916	10103.063	10101.264
	Average	10100.405	10100.330	10100.670
NI	Best	44	30	16
	Worst	500	500	125
	Average	166.28	201.14	31.62

Table 9shows the best, worst, and average values for P_{all}, F_{all}, and *NI* calculated using PSO, MFO, and FPA optimization techniques for Event 2-B. The results in Event 2-B show a pattern similar to that of Event 2-A. In this event, FPA still produces the smallest F_{all} compared with MFO and PSO techniques. MFO is recorded as the most expensive, calculating RM131398.47 for worst-case generation cost. PSO, MFO, and FPA have slight losses in generated power but the worst cases of P_L for all three optimization techniques do not exceed 0.05% of P_D. FPA method remainsthe winner in terms of *NI*, with five- and six-times faster generation compared with PSO and MFO, respectively. From the results of Events 2-A and 2-B, FPA is the most suitable optimization technique to calculate the cheapest F_{all} without compromising P_D and the smallest *NI* compared with PSO and MFO.

6. CONCLUSION

This study proposes a power scheduling strategy using FPA to achieve optimum power output by generator units at minimum power generation costs for non-smooth ED problems. Testsare carried out in MATLAB environment using two test systems with two different power demands each. The results show that PSO, MFO, and FPA successfully generate P_{all} that is almost the same amount as P_D, with acceptable P_L. In terms of cost, FPA outperforms PSO and MFO in providing lower F_{all} for the same P_D. In terms of *NI*, FPA can solve computational simulations faster compared with PSO and MFO. In conclusion, FPA is the most appropriate technique in power scheduling for ED problems in power systems.

APPENDIX

See Table A1 and A2.

Table A1: Characteristics of Forty Generators System [9]

Unit	P_{min}(MW)	P_{max}(MW)	a_i (RM/h)	b_i(RM/MWh)	c_i(RM/(MW)^{2}h)	d_i(RM/h)	e_i(rad/MW)
1	36	114	94.705	6.73	0.00690	100	0.084
2	36	114	94.705	6.73	0.00690	100	0.084
3	60	120	309.540	7.07	0.02028	100	0.084
4	80	190	369.030	8.18	0.00942	150	0.063
5	47	97	148.890	5.35	0.01140	120	0.077
6	68	140	222.330	8.05	0.01142	100	0.084
7	110	300	287.710	8.03	0.00357	200	0.042
8	135	300	391.980	6.99	0.00492	200	0.042
9	135	300	455.760	6.60	0.00573	200	0.042
10	130	300	722.820	12.9	0.00605	200	0.042
11	94	375	635.200	12.9	0.00515	200	0.042
12	94	375	654.690	12.8	0.00569	200	0.042
13	125	500	913.400	12.5	0.00421	300	0.035
14	125	500	1760.400	8.84	0.00752	300	0.035
15	125	500	1760.400	8.84	0.00752	300	0.035
16	125	500	1760.400	8.84	0.00752	300	0.035
17	220	500	647.850	7.97	0.00313	300	0.035
18	220	500	649.690	7.95	0.00313	300	0.035
19	242	550	647.830	7.97	0.00313	300	0.035
20	242	550	647.810	7.97	0.00313	300	0.035
21	254	550	785.960	6.63	0.00298	300	0.035
22	254	550	785.960	6.63	0.00298	300	0.035
23	254	550	794.530	6.66	0.00284	300	0.035
24	254	550	794.530	6.66	0.00284	300	0.035
25	254	550	801.320	7.10	0.00277	300	0.035
26	254	550	801.320	7.10	0.00277	300	0.035
27	10	150	1055.100	3.33	0.52124	120	0.077
28	10	150	1055.100	3.33	0.52124	120	0.077
29	10	150	1055.100	3.33	0.52124	120	0.077
30	47	97	148.890	5.35	0.01140	120	0.077
31	60	190	222.920	6.43	0.00160	150	0.063
32	60	190	222.920	6.43	0.00160	150	0.063
33	60	190	222.920	6.43	0.00160	150	0.063
34	90	200	107.870	8.95	0.00010	200	0.042
35	90	200	116.580	8.62	0.00010	200	0.042
36	90	200	116.580	8.62	0.00010	200	0.042
37	25	110	307.450	5.88	0.01610	80	0.098
38	25	110	307.450	5.88	0.01610	80	0.098
39	25	110	307.450	5.88	0.01610	80	0.098
40	242	550	647.830	7.97	0.00313	300	0.035

Table A2: Characteristics of Ten Generators System [9]

Unit	P_{min} (MW)	P_{max} (MW)	a_i (RM/h)	b_i (RM/MWh)	c_i (RM/(MW)^{2}h)	d_i (RM/h)	e_i (rad/MW)
1	10	55	1000.403	40.5407	0.12951	33	0.0174
2	20	80	950.606	39.5804	0.10908	25	0.0178
3	47	120	900.705	36.5104	0.12511	32	0.0162
4	20	130	800.705	39.5104	0.12111	30	0.0168
5	50	160	756.799	38.5390	0.15247	30	0.0148
6	70	240	451.325	46.1592	0.10587	20	0.0163
7	60	300	1243.531	38.3055	0.03546	20	0.0152
8	70	340	1049.998	40.3965	0.02803	30	0.0128
9	135	470	1658.569	36.3278	0.02111	60	0.0136
10	150	470	1356.659	38.2704	0.01799	40	0.0141

ACKNOWLEDGEMENT

This study is funded by the Ministry of Education Malaysia (FRGS/1/2018/TK04/UKM/02/7).

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