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ORIGINAL ARTICLE

A Non-Convex Economic Dispatch Problem with Point-Valve Effect Using a Wind-Driven Optimisation Approach

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Abstract

This study presents the efficiency of the wind-driven optimisation (WDO) approach in solving non-convex economic dispatch problems with point-valve effect. The best economic dispatch for a power system is one wherein the system can generate energy at a low cost. The calculation of the generating cost is subject to a number of constraints, such as the power demand for the entire system and the generation limit for each generator unit in the system. In addition, the system should also produce low power loss. The WDO optimisation technique is developed based on the concept of natural wind movement, which serves as a stabiliser to equalise the inequality of air pressure in the atmosphere. One major advantage of WDO over other techniques is its search accuracy. The proposed algorithm has been implemented in two systems, namely, the 10-generator and 40-generator systems. Both systems were tested in a Matlab environment. To highlight the capabilities of WDO, the results using this proposed technique are compared with the results obtained using flower pollination algorithm, moth flame optimisation, particle swarm optimisation and evolutionary programming techniques to determine the efficiency of the proposed approach in solving economic dispatch. The simulation results show the capability of WDO in determining the optimal power generation value with minimum generation cost and low rate of power loss.

Keywords Non-convex problem formulation · Wind driven optimisation · Flower pollination algorithm · Moth flame optimisation · Particle swarm optimisation · Evolutionary programming

1 Introduction

With the simultaneous increase of economic and population growth, the demand for electricity in a country is also expected to rise every year. However, in early 2020, the world was shocked by the outbreak of COVID-19, which was later declared a pandemic by the World Health Organisation (WHO). The spread of this pandemic has significantly affected power sectors worldwide. Most countries have declared lockdowns for prolonged periods, leading to a significant decline in energy consumption in the industrial and commercial sectors. However, as a result of this lockdown, the workforce has to manage their work from their own homes, paving the way for the so-called 'work-from-home' concept. This has resulted in increased energy demand in residential areas. Such developments have urged utility companies to improve their power grid networks and restructure their power generation scheduling.

Economic Dispatch (ED) schedules the power unit operations to meet a specific power demand whilst also imposing a minimum fuel cost. Categorised as a type of optimisation problem, ED solutions using optimisation can be divided into mathematical and heuristic techniques. Mathematical techniques include linear [1, 2], quadratic [3] and mixed-integer [4] programming. These traditional ED solutions, however, are time-consuming, unable to solve non-linear cost functions and can only provide suboptimal solutions. Such disadvantages have led scientists to introduce heuristic

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approaches, in which ED problems can be categorised as smooth 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 have been successfully solved using heuristic techniques, as respectively reported in [5, 6] and [7–10].

Artificial intelligence (AI) is widely used in the field of power systems. Amongst the techniques used are flower pollination algorithm (FPA) [11–14], moth flame optimisation (MFO) [15–18], particle swarm optimisation (PSO) [19–22] and evolutionary programming (EP) [23–26]. The FPA optimisation technique is developed based on the transfer of pollen from one flower to another on the same tree or another tree using natural pollinators, such as honey bees, birds, water or wind. MFO is inspired by moth navigation methods in nature and is known as a transverse orientation, ensuring that a moth is at a constant angle to the source of light, such as the moon and the candle flame for orientation. The PSO technique, which is also based on the movement of animal, is inspired by the feeding process of certain animals, such as swarming birds and schooling fish. EP is one of the evolutionary computing, which uses the models of biological evolutionary process such as mutation, for the solution of complex engineering problems. In the present study, a new metaheuristic-based method called wind driven optimisation (WDO) is introduced [27–30]. WDO is based on the concept of natural wind movement, which serves as a stabiliser to equalise the inequality of air pressure in the atmosphere. One advantage of WDO over other techniques is its search accuracy. In particular, its optimisation capabilities have been proven in various optimisation problems, such as economics delivery, engineering design and medical applications.

The current study proposes efficient techniques for calculating optimal, non-smooth power generation capacity based on power demand as well as the constraints of each generator unit, using the WDO optimisation approach. Test systems using 10- and 40-unit power generators are simulated using MATLAB. The objective function of this optimisation is to minimise the total cost of power generation. To determine the performance of the proposed technique, the results of using the WDO technique are compared with those obtained via FPA, MFO, PSO and EP.

The rest of the paper is organised into sections. Section 2 presents the non-convex problem formulation for ED. Section 3 explains the WDO algorithm. Section 4 provides the simulation results and discussions. Finally, Sect. 5 presents the conclusions.

2 Formulation of Economic Dispatch

In economic dispatch, energy generation planning is focused on coordinating energy production for each generation unit within a system. The amount of energy generated should exceed the power demand that has been set at an early stage. However, the production of high surplus energy will result in financial losses to energy operators. In addition, each generator unit has its own generating cost characteristics and different generating capacities. The generating unit cost calculation method can be divided into two formulations: convex and non-convex problem formulations.

In the fundamental concept of convex problem formulation, the cost function of each generator can be presented by a simple quadratic function presented by Eq. (1):

$$\mathrm{Cost}_c\left(P_i\right) = a_{c,i} + b_{c,i}P_i + c_{c,i}P_i^2, \tag{1}$$

where $Cost_c(P_i)$ is the convex production cost of P_i in \$ per hour, P_i is the real power output of the ith generator in MW, and $a_{c,i}$, $b_{c,i}$, and $c_{c,I}$ are three of the convex generation cost coefficients of P_i. The operating limits of P_i can be presented as follows:

$$P_{i,\min} \le P_i \le P_{i,\max}, \tag{2}$$

where the minimum and maximum operating limits of P_i are $P_{i,min}$ and $P_{i,max}$, respectively.

According to its basic concept, the fuel cost function per generating unit is considered to increase quadratically; however, it cannot solve the ED problem practically without considering the point-valve effect. Such an effect can cause the generator input–output curve to become more complicated. This method of calculation based on the point-valve effect is called non-convex problem formulation. To model the point-valve effect, a recurring rectified sinusoid contribution was added to the Eq. (1), represented by Eq. (3):

$$\mathrm{Cost}_n\left(P_i\right) = a_{n,i} + b_{n,i}P_i + c_{n,i}P_i^2 + \left|e_{n,i}\sin\left(f_{n,i}\left(P_{i,\min} - P_i\right)\right)\right| \tag{3}$$

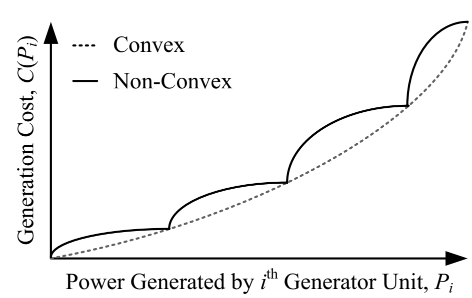

Fig. 1 Cost function according to the point-valve effect system (non-convex) and without point-valve effect system (convex)

where $Cost_n(P_i)$ is the non-convex production cost of P_i, in \$ per hour. Five of the non-convex generation cost coefficients of P_i are represented by $a_{n,i}$, $b_{n,i}$, $c_{n,i}$, $e_{n,i}$ and $f_{n,i}$, respectively. The obvious difference between these two problem formulations is the presence of a sinusoidal function on the cost equation for the non-convex problem formulation.

Figure 1 illustrates the convex problem formulations (systems without point-valve effects) and non-convex problem formulations (systems with point-valve effects). As can be seen, the cost rate for the system without the point-valve effect increases quadratically. In comparison, the cost rate for a system with a point-valve effect goes up and down (like a hill) along a quadratic line. This is the effect of the valve opening according to the requested power generation. In this study, the calculation of the generation cost of each generator unit will use the concept of non-convex problem formulation.

Based on the calculated production cost of every generator using non-convex problem formulations, the total production cost $Cost_T$ with all n generators in the system can be expressed as follows:

$$\mathrm{Cost}_T = \mathrm{Cost}_n\left(P_1\right) + \mathrm{Cost}_n\left(P_2\right) + \cdots\cdots + \mathrm{Cost}_n\left(P_n\right). \tag{4}$$

The correlations among the total amount of power generated by all unit P_T, total power demand P_D, and power losses P_L can be expressed as

$$P_T = P_1 + P_2 + \cdots P_n = P_D + P_L. \tag{5}$$

Apart from producing low generation costs, a good generation system also produces low P_L.

3 Wind Driven Optimisation Techniques

This study proposes a new technique based on wind movement called WDO. The basic optimisation method for WDO and the stopping criteria for finding the best generation cost are described in the next subtopic.

3.1 Wind Driven Optimisation

The concept of WDO was first developed by Zikri Bayraktar in 2010. It is based on the concept of natural wind movement, which serves as a stabiliser to equalise the inequality of air pressure in the atmosphere. Wind blows from a high- to a low-pressure area, according to a velocity that is directly proportional to the pressure gradient (the higher the pressure difference, the stronger the wind blows). Wind can be thought of as moving horizontally by assuming that the horizontal motion of the air is stronger than its vertical motion. The main principle behind the WDO technique is Newton's second law of motion:

$$\rho\vec{a} = \sum \vec{F_i}, \tag{6}$$

where a is the acceleration vector, ρ is the air density for an element with a very small volume and F_i is the force acting on the mass. Air pressure, density and temperature are related by an equation according to the ideal gas law expressed as

$$P = \rho RT, \tag{7}$$

where P, R and T represent pressure, universal gas constant and temperature, respectively.

In Eq. (6), the main forces that cause the wind blowing in a direction to deviate from that direction can be broken down into four: pressure gradient force (F_{PG}), frictional force (F_F), gravitational force (F_G) and coriolis force (F_C). Their corresponding force equations are given below:

$$\vec{F}_{PG} = -\nabla P\delta V, \tag{8}$$

$$\vec{F}_C = -2\Omega \times \vec{u}, \tag{9}$$

$$\vec{F}_G = \rho\delta V\vec{g}, \tag{10}$$

$$\vec{F}_F = -\rho\alpha\vec{u}, \tag{11}$$

where ∇P is the pressure gradient, δV is a very small volume of air, Ω represents the rotation of the earth, u is the wind velocity vector and g is the gravitational acceleration. The combination of Eqs. (6) and (8)–(11) produces an equation represented by Eq. (12) below:

$$\rho\vec{u}\Delta t = -\nabla P\delta V - 2\Omega \times \vec{u} + \rho\delta V\vec{g} - \rho\alpha\vec{u}. \tag{12}$$

A packet of air moving with the wind can be considered very small. The unit step of time, Δt can also be considered equal to 1. The combination of Eqs. (7) and (12) produces the following equation:

$$\begin{aligned}\vec{u}_{new} = -g\vec{x}_{old} + (1-\alpha)\vec{u}_{old} + \left|1 - \frac{P_{\max}}{P_{old}}\right| \\ RT\left(x_{\max} - x_{old}\right) - \frac{cu_{old}^{other\,\dim}}{P_{old}},\end{aligned} \tag{13}$$

where u_{new} and u_{old} are the updated velocity and the current velocity, respectively; x_{old} and x_{max} are the current location and the highest-pressure location of the air pack, respectively; P_{max} and P_{old} are the maximum pressure and the pressure at the current location, respectively; T is the temperature; and R, α and c are constants.

The pressure value in Eq. (13) is usually high. Therefore, the new velocity estimations will also be high. This causes the performance level of the WDO to decrease. To solve this problem, the use of pressure values will be replaced by method based on ranking of air parcel [30]. The air parcel population is ranked in descending order based on its pressure value. Equation (13) is rearranged into the following equation:

$$\vec{u}_{new} = -g\vec{x}_{old} + (1-\alpha)\vec{u}_{old} + \left|1-\frac{1}{k}\right| RT\left(x_{\max} - x_{old}\right) - \frac{cu_{old}^{other\,\dim}}{k}. \tag{14}$$

Here, k denotes the ranking between all air parcels ($k = 1, 2,\ldots, 20$). The following equation is used to update the position of the air pack:

$$\vec{x}_{new} = \vec{x}_{old} + \vec{u}_{new} \times \Delta t. \tag{15}$$

The potential trajectories of the pressure gradient force, coriolis force, frictional force and gravitational force in WDO are shown in Fig. 2.

The flow chart of the optimisation process using the WOA technique is shown in Fig. 3. In this study, the ability of WOA to find the optimal generation cost value is compared with that of four other selected optimisation techniques, namely, FPA, MFO, PSO and EP. Detailed explanations of the FPA, MFO, PSO and EP approaches can be found in [11, 15, 19] and [23], respectively.

3.2 Stopping Criteria

In this study, a total of 100 tests were simulated to obtain optimal results for each technique in every case. The

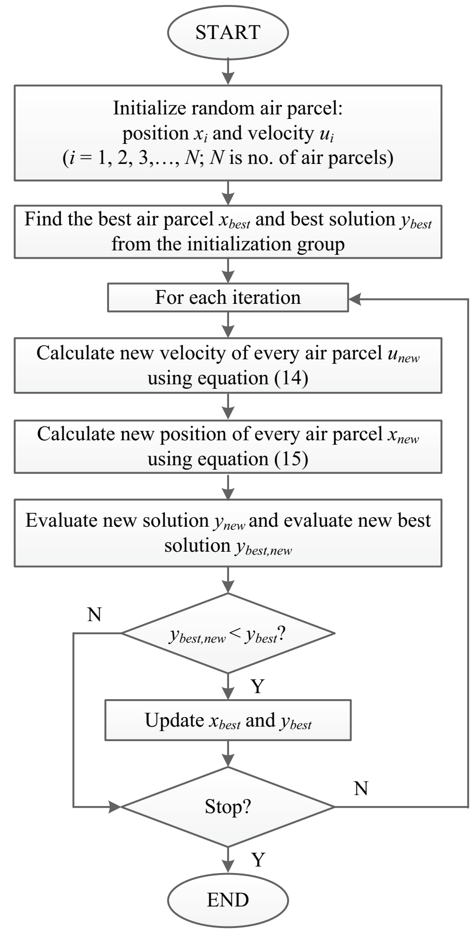

Fig. 3 The flow chart of the optimisation process using WOA

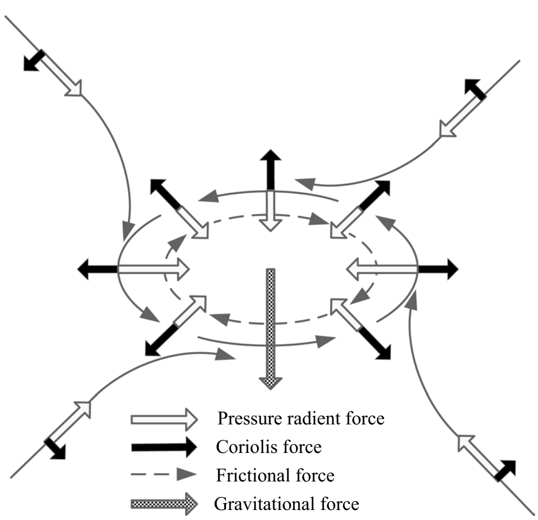

Fig. 2 Potential trajectories of the pressure gradient force, coriolis force, frictional force and gravitational force in WDO

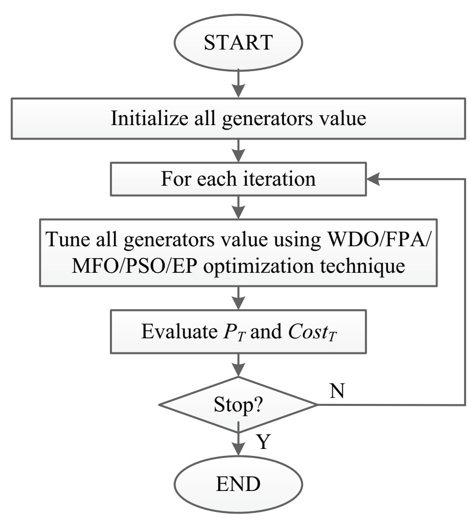

Fig. 4 The flow chart of the calculation process of P_T and $Cost_T$

Table 1 Lists of test systems, cases and P_D values

Test System	Cases	P_D (MW)
Ten Generators	Case 1	1400
	Case 2	2050
Forty Generators	Case 3	8700
	Case 4	9650

Table 2 List of parameter values used in WDO, FPA, MFO, PSO and EP

WDO			MFO		
RT	RT coefficient	35	β	Constant	1
g	Gravity constant	0.01	τ	Random value	(0,1]
α	Alpha	0.9	EP		
c	Coriolis effect	0.95	β	Scaling factor	0.05
v_{max}	Maximum speed	0.1	PSO		
FPA			ω	Inertia weight	0.05
p	Boundary value	0.7	c_1	Accelerating coefficient	0.5
ε	Uniform distribution	(0,1]	c_2	Accelerating coefficient	0.5

maximum number of iterations per case is set at 300 iterations. Based on 100 tests for each of these cases, a consistent result can be obtained. Figure 4 shows the flow chart of the calculation process of P_T and $Cost_T$.

As shown in Fig. 4, there are two criteria for the optimisation process to stop: (i) the difference between the maximum and minimum generation cost is less than 0.1% of minimum $Cost_T$, and (ii) the current iteration is equal to the maximum number of iterations.

4 Results and Discussions

There were two test systems involved, namely, the 10- and 40-generator systems. Cases 1-A and 1-B were run using a 10-generator test system, whilst Cases 2-A and 2-B were run using a 40-generator test system. The simulations were conducted using Matlab software in a computer with Intel (R) Core (TM) i5-8250U processing specifications. Table 1 illustrates all the test systems, cases and specific power demand P_D values.

Table 2 shows the list of parameter values used in WDO, FPA, MFO, PSO and EP in this study.

Table 3 and Table 4 present the fuel cost coefficients ($a_{n,i}$, $b_{n,i}$, $c_{n,i}$, $e_{n,i}$ and $f_{n,i}$) with minimum and maximum power limits (P_{min} and P_{max}) for each generator unit in ten-generator and forty-generator test systems, respectively [31].

Based on the simulations conducted, the iteration period taken by the EP technique is the lowest amongst the five approaches used, i.e. 10–20 iterations. For the WDO, FPA and PSO methods, the range of the number of iterations to complete the simulation is 50–100 iterations. The MFO approach requires the highest number of iterations, i.e. 50–150 iterations.

Table 5 shows the optimisation results of 10 generator values; total power generation, P_T; and power loss, P_L for Case 1 using the WDO, FPA, PSO, MFO and EP techniques. This value was obtained from 100 simulations conducted for each technique. If we compare the selected generation values for all 10 generators, there are very significant differences among these five approaches. Although the generation value for each of these generators is different, the majority of the methods achieve the same P_T value as the prescribed P_D, which is 1400 MW. The P_L results obtained using PSO are the best, resulting in zero power loss. This is followed by FPA, MFO and EP. WDO produces the highest power loss: 77.6 kW. However, this power loss value is very minimal

Table 3 Power limits and fuel cost coefficients with valve-point effect in ten-generator test system

Unit	Power limits		Fuel cost coefficients with valve-point effect				
	P_{min} (MW)	P_{max} (MW)	$a_{n,i}$ ($/h)	$b_{n,i}$ ($/MWh)	$c_{n,i}$ ($/(MW)^2 h)	$d_{n,i}$ ($/h)	$e_{n,i}$ (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

Table 4 Power limits and fuel cost coefficients with valve-point effect in forty-generator test system

Unit	Power limits		Fuel cost coefficients with valve-point effect				
	P_{min} (MW)	P_{max} (MW)	$a_{n,i}$ ($/h)	$b_{n,i}$ ($/MWh)	$c_{n,i}$ ($/(MW)^2 h)	$d_{n,i}$ ($/h)	$e_{n,i}$ (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	130	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	635.200	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

compared to P_D (only representing 0.006% of the P_D value) and is acceptable.

Table 6 shows the three optimal $Cost_T$ generation cost values (best, worst and average) for Case 1. There are three optimal $Cost_T$ values observed, namely, best, worst and average $Cost_T$. From the perspective of generation cost based on the best $Cost_T$ value, the WDO method yields the cheapest cost of $73,550.10, followed by FPA, PSO, EP and finally MFO. The cost difference between WDO and MFO is $1,616.40, of which the use of WDO saves 2.15% compared to MFO. For the worst $Cost_T$ value, PSO provides the cheapest generation cost, followed by FPA, WDO, EP and MFO. The PSO performance is also excellent from the perspective of the average $Cost_T$, which is $74,046.00, compared to MFO which yields the most expensive average $Cost_T$ of $75,988.90.

Table 5 Optimal values of ten generators, P_T and P_L for Case 1

Generators	Power Output (MW)				
	WDO	FPA	PSO	EP	MFO
P_1	37.2460	32.8694	28.7449	13.9650	45.6974
P_2	52.0730	42.1987	41.9311	41.2693	52.1088
P_3	55.0002	61.4683	71.6364	94.6273	76.6114
P_4	44.1233	35.3087	56.9393	89.4375	69.8739
P_5	59.0050	57.5162	50.0248	50.0169	103.4620
P_6	70.1490	71.9811	70.8618	89.1754	115.7997
P_7	176.7250	184.3209	169.5514	90.9592	181.7518
P_8	208.3102	194.2257	207.1486	155.3605	176.4693
P_9	357.6415	368.1389	337.8918	422.3723	260.8406
P_{10}	339.8043	351.9893	365.2700	352.8614	317.4054
P_T	1400.1	1400.0	1400.0	1400.0	1400.0
P_L	0.0776	0.0172	0.0000	0.0447	0.0203

Table 6 $Cost_T$ (best, worst and average) for Case 1

$Cost_T$ ($\times 10^3$ \$)	WDO	FPA	PSO	EP	MFO
Best Value	73.5501	73.5681	73.5805	74.6649	75.1665
Worst Value	75.2377	75.1034	74.5993	76.2122	76.9685
Average Value	74.2104	74.1112	74.0460	75.7129	75.9889

Table 7 Optimal values of ten generators for Case 2

Generators	Power Output (MW)				
	WDO	FPA	PSO	EP	MFO
P_1	54.7399	53.1208	46.8454	31.2615	53.8569
P_2	79.8961	77.2853	69.6440	78.4024	57.0711
P_3	105.4016	118.7199	103.9364	74.0878	99.9383
P_4	91.0725	94.7526	97.8784	128.9845	97.2851
P_5	68.1580	81.2763	78.9019	76.5929	141.6828
P_6	71.6061	75.1139	92.2134	150.7565	192.0888
P_7	299.7558	296.6702	298.1497	284.8565	251.2110
P_8	339.8989	338.3731	340.0000	315.9169	317.0608
P_9	469.9720	467.8319	468.6216	452.7929	436.7844
P_{10}	469.5987	447.2566	453.8091	456.4505	403.0211
P_T	2050.1	2050.4	2050.0	2050.1	2050.0
P_L	0.0996	0.4006	0.0000	0.1024	0.0002

WDO ranks third in the five methods compared. In this Case 1, PSO gives the best and worst $Cost_T$ difference. This indicates that in Case 1, PSO is able to maintain optimal value consistency in the 100 simulations run. This is followed by FPA, EP, WDO and MFO. Although less prominent for the worst and average $Cost_T$ values, WDO excelled in terms of best $Cost_T$, thus making it the best optimisation approach amongst the five methods compared.

Table 8 $Cost_T$ (best, worst and average) for Case 2

$Cost_T$ ($\times 10^3$ \$)	WDO	FPA	PSO	EP	MFO
Best Value	109.1962	109.4541	109.4660	110.5981	112.4619
Worst Value	111.2749	110.3995	110.4337	113.4144	114.7050
Average Value	109.9090	110.0390	110.1242	112.1201	113.8818

The optimum values of 10 generators, P_T and P_L using WDO, FPA, PSO, EP and MFO for Case 2 are shown in Table 7. The five methods successfully tuned the values for each generator to produce the total generating power as set by P_D which is 2,050 MW. PSO produced the lowest P_L i.e. zero loss, followed by MFO, WDO, EP and FPA. The value of P_L by FPA is 400.6 kW, which is 0.02% of P_D. Despite the occurrence of power loss, the values given by the four techniques other than PSO are all extremely minimal and acceptable.

Table 8 tabulates the optimal $Cost_T$ (best, worst and average) based on 100 simulation tests for Case 2. On the one hand, for Case 2, the best and the average $Cost_T$ values by WDO, which are \$109,162.90 and \$109,909.00, respectively, are both considered excellent by producing the lowest values amongst the five methods. MFO, on the other hand, is an optimisation method that tunes the generator unit with the most expensive $Cost_T$ amongst the best, worst and average optimal values. Amongst the five worst optimal values, WDO also provides the lowest generation cost values, followed by FPA, EP, PSO and MFO. Based on the results obtained for Case 2, WDO is the best approach among those compared in terms of tuning the generator value to produce the lowest generation cost.

Table 9 shows the optimum values of 40 generators using WDO for Case 3. As a proposed technique, the generator values calculated by WDO are tabulated in this table.

The values for total generation, P_T; power loss, P_L; and optimal fuel cost, $Cost_T$ (best, worst and average) based on 100 simulation tests for the five optimisation techniques for Case 3 are shown in Table 10. As can be seen, WDO and FPA techniques generate total power values that are approximately similar to the power demand, P_D, which is 8,700 MW, with P_L values at 39.9 and 28.1 kW, respectively. This is followed by PSO, EP and MFO with P_L values at 203.3, 871.4 and 954.3 kW, respectively. The highest P_L value is produced by the MFO, which is about 0.01% of the P_D value—a minimal and acceptable value of power loss. From the best $Cost_T$ generation cost perspective, WDO produces the cheapest cost at \$104,503.90, followed by FPA, PSO, EP and MFO.

Table 10 also shows that the difference between the best $cost_T$ and worst $cost_T$ values (i.e. \$838), which is calculated

Table 9 Optimal generator values using WDO for Case 3

Gen	Values (MW)	Gen	Values (MW)	Gen	Values (MW)	Gen	Values (MW)
P_1	91.7379	P_{11}	94.2034	P_{21}	527.9771	P_{31}	187.5987
P_2	37.6354	P_{12}	94.2941	P_{22}	541.8251	P_{32}	177.6737
P_3	67.6266	P_{13}	125.2984	P_{23}	530.5006	P_{33}	66.8977
P_4	80.0122	P_{14}	125.1635	P_{24}	545.0939	P_{34}	91.4794
P_5	94.4204	P_{15}	385.1753	P_{25}	533.2426	P_{35}	160.6316
P_6	68.0171	P_{16}	148.4389	P_{26}	461.4438	P_{36}	90.0110
P_7	144.6910	P_{17}	399.0958	P_{27}	10.0316	P_{37}	103.5682
P_8	266.7026	P_{18}	487.6544	P_{28}	10.6505	P_{38}	25.1094
P_9	134.8687	P_{19}	515.6547	P_{29}	10.0184	P_{39}	26.5686
P_{10}	130.3725	P_{20}	47.0359	P_{30}	54.2192	P_{40}	507.3999

Table 10 P_T, P_L and $Cost_T$ (best, worst and average) for Case 3

Generators	Power Output (MW)				
	WDO	FPA	PSO	EP	MFO
P_T (MW)	8700.0	8700.0	8700.2	8700.9	8701.0
P_L (MW)	0.0399	0.0281	0.2033	0.8714	0.9543
Best $cost_T$ ($\times 10^3$ \$)	104.5039	104.7626	105.8389	112.7587	112.1324
Worst $cost_T$ ($\times 10^3$ \$)	112.0477	115.8665	109.6689	113.5967	113.9424
Average $cost_T$ ($\times 10^3$ \$)	108.3233	109.1284	107.0617	113.1129	115.5889

Table 11 Optimal generator values using WDO for Case 4

Gen	Values (MW)	Gen	Values (MW)	Gen	Values (MW)	Gen	Values (MW)
P_1	105.5497	P_{11}	96.1000	P_{21}	535.0146	P_{31}	189.9561
P_2	113.724	P_{12}	132.9019	P_{22}	546.4675	P_{32}	170.6419
P_3	64.3305	P_{13}	125.0737	P_{23}	524.4567	P_{33}	75.3798
P_4	136.119	P_{14}	395.3443	P_{24}	524.9659	P_{34}	199.7569
P_5	61.0432	P_{15}	370.5575	P_{25}	540.6237	P_{35}	120.7023
P_6	71.3441	P_{16}	131.8998	P_{26}	547.6057	P_{36}	196.2475
P_7	187.358	P_{17}	493.3949	P_{27}	11.4685	P_{37}	94.2439
P_8	284.0464	P_{18}	477.9911	P_{28}	13.7626	P_{38}	109.7994
P_9	134.5449	P_{19}	549.8370	P_{29}	18.7203	P_{39}	108.9533
P_{10}	241.832	P_{20}	538.0521	P_{30}	92.0219	P_{40}	518.4186

Table 12 P_T, P_L, and $Cost_T$ (best, worst and average) for Case 4

Generators	Power Output (MW)				
	WDO	FPA	PSO	EP	MFO
P_T	9850.3	9850.1	9850.1	9850.5	9850.1
P_L	0.2515	0.1171	0.1207	0.4850	0.1134
Best $cost_T$ ($\times 10^3$ \$)	117.8404	118.9734	119.6477	125.9508	126.8486
Worst $cost_T$ ($\times 10^3$ \$)	125.0225	125.5121	121.4457	129.4023	130.3201
Average $cost_T$ ($\times 10^3$ \$)	122.4021	122.4920	122.4960	128.5443	128.6714

using EP, is the smallest amongst the five methods. This indicates that for Case 3, the values based on the EP technique are the most consistent values for the entire 100 simulations conducted. Meanwhile, FPA has the largest best and worst $cost_T$ difference of \$1,110.39. Despite providing the most consistent value, EP provides the most expensive $cost_T$ of the five techniques for this case. Therefore, the best technique that provides the cheapest $cost_T$ is WDO, followed by FPA, PSO and MFO.

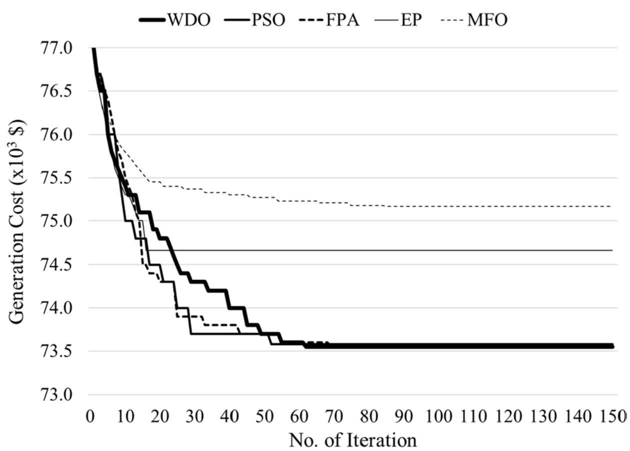

Fig. 5 The flow chart of the calculation process of P_T and $Cost_T$

The optimum values of 40 generators (Set 2) using WDO for Case 4 are tabulated in Table 11.

The optimal P_T, P_L and $Cost_T$ values (best, worst and average) for Case 4 are shown in Table 12. As can be seen, all techniques are capable of achieving the P_D set at 9850 MW. Of the five methods used, MFO has the lowest P_L of 113.4 kW, followed by FPA, PSO and WDO. EP tuned the highest P_L at 485.0 kW, which is 0.005% of the P_D value. This indicates that all the P_L values produced by the five optimisation methods in this case are minimal and acceptable. Despite giving the lowest P_L, the MFO yields a $Cost_T$ of 126.8486 MW, which is the most expensive amongst the five methods simulated. In Case 4, PSO still retains its potential as a method that provides the most consistent $Cost_T$ results in all 100 simulations conducted, i.e. in the range between 119.6477–121.4457 MW. Overall, WDO tuned 40 generators to produce the lowest values among the best, worst and average $Cost_T$ values at 117.8404, 125.0225 and 122.4021 MW, respectively. This makes WDO as the technique of choice in tuning the generator unit in producing the cheapest generation cost according to the P_D that has been set with minimum P_L.

Figure 5 shows the convergence curves of all five optimization techniques which give the best $cost_T$ for Case 1. From the figure, EP converge in 16 iterations, followed by PSO (52 iterations), WDO (62 iterations), FPA (69 iterations) and MFO (91 iterations). Although EP gives the fastest technique to converge, it could not give the lowest generation cost compared to the other four methods. On the other hand, WDO, FPA and PSO are converge almost the same number of iterations. From this result, this indicates the WDO period for convergence is within an acceptable range and is almost identical to other techniques such as FPA and PSO.

5 Conclusion

This study proposed a power scheduling strategy using WDO to achieve optimal power generation by generator units with minimum power generation cost based on non-convex problem formulation. The WDO technique was compared with four selected techniques, namely, FPA, MFO, PSO and EP. The 10- and 40-generator systems, each with two different power demands, were selected as test systems and implemented using MATLAB. Results showed that the five approaches tested successfully produced energies that were almost equal to the energy demands, with extremely low power losses. In terms of generation costs, the majority of scenarios demonstrated that WDO outperforms the other four methods in providing lower generation costs for the same energy demand. From the perspective of iteration time, the WDO capability is found to be equivalent to most of the techniques compared, which requires between 50–100 iterations to complete the calculation. In conclusion, WDO is the most accurate technique that can be used in power scheduling for economic dispatch problems in power systems that consider the point-valve effect.

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