Handling Economic Load Dispatch Problem Using Novel Metaheuristic Called Iteration Shift Algorithm

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***Abstract*—Economic load dispatch (ELD) problem is an important optimization problem in power systems. Its objective is to minimize the total power generating cost. Metaheuristics are commonly used to overcome this problem. Unfortunately, many of these metaheuristics are old. On the other hand, there are many new metaheuristics initiated in recent years but new metaheuristics that use ELD problem as their practical use case in their first appearance is hard to find. Based on it, this work initiates a new swarm-based metaheuristics called iteration shift algorithm (ISA) that uses ELD problem to assess its efficacy besides the set of 23 functions representing the theoretical use case. A new approach in utilizing iteration stochastically to determine the strategy is also initiated. There are five new metaheuristics chosen as contenders of ISA in this work: golden search optimization (GSO), language education optimization (LEO), walrus optimization algorithm (WaOA), lyrebird optimization algorithm (LOA), and total interaction algorithm (TIA). The result of theoretical case appraisal shows that ISA is better than GSO, LEO, WaOA, LOA, and TIA in 21, 9, 11, 16, and 14 functions respectively. Meanwhile, ISA is competitive in solving ELD problem with 10 generating units after LEO and WaOA.**

***Index Terms*—economic load dispatch problem, power system, optimization, metaheuristic, swarm intelligence.**

I. Introduction

Economic load dispatch (ELD) problem is an important optimization problem in the power system sector. It shares the total power demand into a certain number of generating units or generators [1]. In general, ELD is a single objective optimization problem whose objective is minimizing the power generating cost which is given in quadratic functions [2]. Meanwhile, in a few studies, ELD problem was transformed into multi objective problem by including the emission cost [3]. In a few studies, a few aspects like power loss or valve point loading [2] are considered.

In general, metaheuristics has become a common optimization tool in solving ELD problems. These metaheuristics can be the local search, evolutionary, or swarm-based ones. Many of these studies utilized old metaheuristics, such as bat algorithm (BA) [4], crow search algorithm (CSA) [2], simulated annealing (SA) [3], particle swarm optimization (PSO) [5], teaching learning-based optimization (TLBO) [6], multi-verse optimization (MVO) [7], and so on. Only a few studies implemented relatively new metaheuristics, such as slime mold algorithm (SMA) [8], technique of narrowing down area (ToNDA) [9], or squirrel search optimizer (SSO) [1].

In recent years, there are a lot of studies constructing new metaheuristic. Many of them were developed based on swarm intelligence, such as northern goshawk optimization (NGO) [10], golden jackal optimization (GJO) [11], migration algorithm (MA) [12], pelican optimization algorithm (POA) [13], fully informed search algorithm (FISA) [14], and so on. As an iterative based optimization, iteration has main objective as a counter. In a few swarm-based metaheuristics that are also enriched with neighborhood search like in Kookaburra optimization algorithm (KOA) [15] and green anaconda optimization (GAO) [16], iteration is also utilized as local search space reducer. Meanwhile, metaheuristics that utilize iteration as determinant to choose tracing strategy is rare to find. The Marine predator algorithm (MPA) [17] is one example of these few metaheuristics.

Moreover, studies constructing new metaheuristic that use ELD problem as practical use case is rare to find. Many of them, which are constructing language education optimization (LEO) [18], walrus optimization algorithm (WaOA) [19], lyrebird optimization algorithm (LOA) [20], prairie dog optimization (PDO) [21], and crayfish optimization algorithm (COA) [22] choose four designs in mechanical engineering (welded beam, tension/compression spring, pressure vessel, and speed reducer). Meanwhile, a few other studies conducted the theoretical case appraisal only, which are found in Komodo Mlipir algorithm (KMA) [23], total interaction algorithm (TIA) [24], golden search algorithm (GSO) [25], coronavirus herd immunity optimizer (CHIO) [26], and so on.

The objective of this study is to develop a new metaheuristic based on swarm intelligence called as iteration shift algorithm (ISA) and implement it to overcome the ELD problem. Then, the contributions of this study are as follows.

- This study proposes a new metaphor free metaheuristic that comprises two directed traces.
- This proposed ISA utilizes iteration not only as a counter but also to determine the chosen strategy between exploration and exploitation in a stochastic manner.
- ISA is implemented to overcome the 23 classic functions representing theoretical optimization

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problems that cover both unimodal problems and multimodal problems.

- ISA is also implemented to overcome the ELD problem that represents practical use case.
- Five recent metaheuristics are chosen as contenders in these appraisals to evaluate the improvement provided by ISA.

The remainder of this paper is arranged as follows. Section two describes the details of the model of ISA, including the concept and formalization through pseudocode and mathematical formulation. Section three presents the appraisals conducted to evaluate the efficacy of ISA including the theoretical case and practical case appraisal. Section four presents a comprehensive investigation regarding the appraisal result, findings, limitations, and computational complexity. In the end, the conclusion and proposal for further studies are summarized in section five.

II. Model

The proposed ISA is developed using the concept of the shifting from exploration to exploration as iteration goes. ISA is also developed using multi search approach so that it comprises two serial traces. The first trace tends to be exploitation. The first trace focuses on the motion toward the better agent. There are two possible leaders in this first trace. The first leader is the best agent. The second leader is the average of all better agents plus the best agent. The second trace tends to be exploration. There are also two possible leaders in this second trace. The first leader is the average of the best agent and two randomly selected agents. The second leader is the average of three randomly selected agents. The annotations used in this paper are shown in Table 1.

The formalization of ISA is given in algorithm 1. As commonly found in any metaheuristic, ISA comprises two phases. The first phase is the initialization which is given in lines 2 and 3. Meanwhile, the second phase is the iteration which is given in lines 6 to 12. The best agent becomes the final solution of ISA. Moreover, the flowchart of ISA is given in Fig. 1.

TABLE I
List of Annotations

Notations	Description
a	agent
A	set of agents (swarm)
a_{best}	the best agent
a_{better}	better agent
A_{better}	set of better agents
a_{lead}	leader
a_{sel}	randomly selected agent
c_1, c_2	first and second candidates
d	dimension
f	objective function
i, j, k	index
lb, ub	lower and upper boundaries
t	iteration
t_{max}	maximum iteration
U_f, U_i, U_p	uniform random (float, integer, population)

The initialization comprises two tasks. The first task is generating an initial solution for each agent which is formalized using (1). Then, the second task is updating the best agent using (2).

$$a_{i,j} = lb_j + U_f(ub_j - lb_j) \quad (1)$$

$$a_{best}' = \begin{cases} a_i, f(a_i) < f(a_{best}) \\ a_{best}, otherwise \end{cases} \quad (2)$$

The first trace is formalized using (3) to (5). Equation (3) states that the first leader is the best agent or the average of all better agents plus the best agent depends on the stochastic task controlled by the iteration. Equation (4) states that the first motion is toward the first leader. Equation (5) states the updating of the agent based on the first candidate.

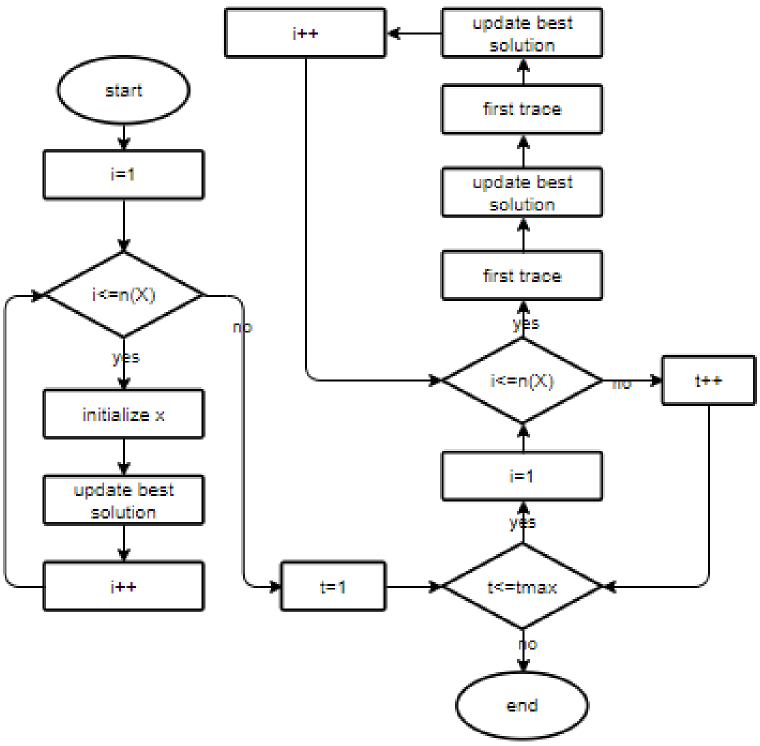

Fig. 1. Flowchart of iteration shift algorithm

algorithm 1: iteration shift algorithm

```
begin
 foreach a_i in A
  initialize a_i
  update a_best
 end for
 for t=1 to t_max
  foreach a_i in A
   perform first trace then update a_best
   perform second trace then update a_best
  end for
 end for
 return a_best
end
```

$$a_{lead1,j} = \begin{cases} a_{best,j}, U_f(0,1) < \frac{t}{t_{max}} \\ \frac{\sum_1^{n(A_{better})} a_{better,k,j} + a_{best,j}}{n(A_{better})+1}, otherwhise \end{cases} \quad (3)$$

$$c_{1,i,j} = a_{i,j} + U_f(0,1)(a_{lead1,j} - U_i(1,2)a_{i,j}) \quad (4)$$

$$a'_{i,j} = \begin{cases} c_{1,i}, f(c_{1,i}) < f(a_i) \\ a_i, otherwise \end{cases} \quad (5)$$

The second trace is formalized using (6) to (9). Equation (6) represents the uniform selection among the swarm. Equation (7) states that the second leader is the average of the best agent plus two randomly selected agents or the average of three randomly selected agents where this decision is controlled stochastically by the iteration. Equation (8) determines the direction of the second trace whether moving toward the second leader or avoiding the second leader. Equation (9) states the updating of the agent based on the second candidate.

$$a_{sel} = U_s(A) \quad (6)$$

$$a_{lead2,j} = \begin{cases} \frac{a_{best,j} + a_{sel1,j} + a_{sel2,j}}{3}, U_f(0,1) < \frac{t}{t_{max}} \\ \frac{a_{sel1,j} + a_{sel2,j} + a_{sel3,j}}{3}, otherwise \end{cases} \quad (7)$$

$$c_{2,i,j} = \begin{cases} a_{i,j} + U_f(0,1)\left(a_{lead2,j} - U_i(1,2)a_{i,j}\right), f(a_{lead2}) < f(a_i) \\ a_{i,j} + U_f(0,1)\left(a_{i,j} - U_i(1,2)a_{lead2,j}\right), otherwise \end{cases} \quad (8)$$

$$a'_{i,j} = \begin{cases} c_{2,i}, f(c_{2,i}) < f(a_i) \\ a_i, otherwise \end{cases} \quad (9)$$

III. RESULT

There are two appraisals that are performed in this work. These appraisals are taken to evaluate the efficacy of the proposed ISA. The first appraisal is the theoretical appraisal, and the second appraisal is the practical appraisal. In the first appraisal, ISA is challenged to overcome the theoretical-unconstrained problems where the set comprising 23 functions is chosen. In the second appraisal, ISA is challenged to overcome the ELD problem. The maximum iteration is set to 20 while the swarm size is set to 5 in both appraisals.

ISA is contended with five new metaheuristics in both appraisals. These five contenders include GSO, LEO, WaOA, LOA, and TIA. All these metaheuristics are new as they are first initiated in 2022 or 2023. All of them are developed based on swarm intelligence. These metaheuristics are chosen due to their specific characteristics.

The set of 23 functions were chosen for several reasons. First, this collection covers various cases of problems. This collection comprises seven high dimension unimodal functions, six high dimension multimodal functions, and ten fixed dimension multimodal functions. Second, this collection is widely employed in many studies introducing new metaheuristic. In this appraisal, the dimension of the high dimension functions is set to 40. A detailed description of these 23 functions is given in Table 2. As given in Table 2, the range of the problem space is various. A few functions have narrow problem space such as Quartic, Rastrigin, Hartman 3, and Hartman 6. On the other hand, a few functions have large problem space such as Schwefel and Griewank.

The result is given in Table 3 to Table 5 while the summary of the superiority of ISA is given in Table 6. Table 3 exhibits the appraisal result on handling the seven high dimension unimodal functions. Table 4 exhibits the appraisal result on handling the six high dimension multimodal functions. Table 5 exhibits the appraisal result on handling ten fixed dimension multimodal functions.

TABLE II
FUNCTIONS

No	Function	Dim	Space	Target
1	Sphere	40	[-100, 100]	0
2	Schwefel 2.22	40	[-100, 100]	0
3	Schwefel 1.2	40	[-100, 100]	0
4	Schwefel 2.21	40	[-100, 100]	0
5	Rosenbrock	40	[-30, 30]	0
6	Step	40	[-100, 100]	0
7	Quartic	40	[-1.28, 1.28]	0
8	Schwefel	40	[-500, 500]	-418.9 x *dim*
9	Ratsrigin	40	[-5.12, 5.12]	0
10	Ackley	40	[-32, 32]	0
11	Griewank	40	[-600, 600]	0
12	Penalized	40	[-50, 50]	0
13	Penalized 2	40	[-50, 50]	0
14	Shekel Foxholes	2	[-65, 65]	1
15	Kowalik	4	[-5, 5]	0.0003
16	Six Hump Camel	2	[-5, 5]	-1.0316
17	Branin	2	[-5, 5]	0.398
18	Goldstein-Price	2	[-2, 2]	3
19	Hartman 3	3	[1, 3]	-3.86
20	Hartman 6	6	[0, 1]	-3.32
21	Shekel 5	4	[0, 10]	-10.1532
22	Shekel 7	4	[0, 10]	-10.4028
23	Shekel 10	4	[0, 10]	-10.5363

TABLE III
APPRAISAL RESULT ON HANDLING SEVEN HIGH DIMENSION UNIMODAL FUNCTIONS

F	Parameter	GSO [25]	LEO [18]	WaOA [19]	LOA [20]	TIA [24]	ISA
1	average score	4.1694×10^4	0.0006	0.0036	2.5023×10^2	0.0000	0.0000
	standard-dev	1.0139×10^4	0.0012	0.0033	2.2587×10^2	0.0000	0.0000
	position	6	3	4	5	1	1
2	average score	3.8936×10^{53}	0.0000	0.0000	0.0646	1.2600×10^{42}	0.0000
	standard-dev	1.1173×10^{54}	0.0000	0.0000	0.2638	5.7740×10^{42}	0.0000
	position	6	1	1	4	5	1
3	average score	1.2361×10^5	3.8159×10^2	8.6711×10^1	3.1443×10^4	8.3084×10^1	2.4699×10^1
	standard-dev	1.4182×10^5	7.9439×10^2	9.8762×10^1	1.3790×10^4	1.7592×10^2	7.5717×10^1
	position	6	4	3	5	2	1
4	average score	6.0824×10^1	0.0554	0.1155	1.4447×10^1	0.0736	0.0011
	standard-dev	8.1893	0.0388	0.0713	6.4847	0.0275	0.0009
	position	6	2	4	5	3	1
5	average score	9.2139×10^7	3.8925×10^1	3.8979×10^1	2.6084×10^4	3.8913×10^1	3.8942×10^1
	standard-dev	4.5608×10^7	0.0472	0.0598	4.0535×10^4	0.0721	0.0251
	position	6	2	4	5	1	3
6	average score	4.0989×10^4	9.3483	8.1100	2.8746×10^2	7.0441	8.2827
	standard-dev	9.4821×10^3	0.9462	0.5786	1.4798×10^2	0.5008	0.4257
	position	6	4	2	5	1	3
7	average score	6.7095×10^1	0.0199	0.0263	0.2178	0.0285	0.0018
	standard-dev	3.4386×10^1	0.0152	0.0150	0.1791	0.0175	0.0108
	position	6	2	3	5	4	1

TABLE IV
APPRAISAL RESULT ON HANDLING SIX HIGH DIMENSION MULTIMODAL FUNCTIONS

F	Parameter	GSO [25]	LEO [18]	WaOA [19]	LOA [20]	TIA [24]	ISA
8	average score	-3.1957×10^3	-3.6814×10^3	-3.1015×10^3	-3.3082×10^3	-2.1595×10^3	-3.0385×10^3
	standard-dev	8.9691×10^2	5.1232×10^2	4.5739×10^2	4.5314×10^2	4.1670×10^2	6.6126×10^2
	position	3	1	4	2	6	5
9	average score	3.9722×10^2	1.6196×10^1	0.9101	2.3289×10^2	0.0124	0.0000
	standard-dev	4.4021×10^1	2.9576×10^1	2.9966	8.1937×10^1	0.0112	0.0001
	position	6	4	3	5	2	1
10	average score	1.9128×10^1	0.0030	0.0111	5.2051	0.0099	0.0001
	standard-dev	0.5706	0.0023	0.0042	2.0492	0.0024	0.0001
	position	6	2	4	5	3	1
11	average score	3.9213×10^2	0.0089	0.0416	3.4835	0.0107	0.0015
	standard-dev	7.4067×10^1	0.0423	0.0758	3.0228	0.0245	0.0065
	position	6	2	4	5	3	1
12	average score	1.3472×10^8	0.9558	0.9816	1.4980×10^1	0.8313	1.0041
	standard-dev	8.4119×10^7	0.1470	0.1448	3.9545×10^1	0.1483	0.1662
	position	6	2	3	5	1	4
13	average score	3.4463×10^8	3.1107	1.9878	2.1427×10^3	3.1717	3.0736
	standard-dev	1.5719×10^8	0.0587	0.2261	7.3164×10^3	0.1268	0.0485
	position	6	3	1	5	4	2

Table 3 shows that ISA is superior in solving high dimension unimodal functions. ISA becomes the best performer in five functions (f_1, f_2, f_3, f_4, and f_7). Moreover, ISA becomes the sole best performer in three functions (f_3, f_4, and f_5). ISA becomes the third best performer in two functions (f_5 and f_6). Although ISA becomes the third best, the efficacy difference between ISA and TIA as the first best performer in these two functions is narrow. Overall, the efficacy difference between the best and worst performers in these high dimension unimodal functions is wide.

Table 4 still indicates the superiority of ISA in solving high dimension multimodal functions. ISA becomes the first best performers in three functions (f_9, f_{10}, and f_{11}). Meanwhile, ISA becomes the second-best performer in f_{13}, fourth best performer in f_{12}, and fifth best performer in f_8. Although ISA is not the best performer, the efficacy difference between ISA and the best performer in these three functions is narrow. In general, the efficacy difference between the best performer and the worst performer is wide in five functions (f_9 to f_{13}). Meanwhile, the efficacy difference between the best and worst performers in f_8 is narrow.

Table 5 shows that ISA is competitive in solving fixed dimension multimodal functions although it is not superior. ISA becomes the first best performer in f_{19} together with LEO, WaOA, LOA, and TIA. ISA becomes the second best in two functions (f14 and f21), third best in one function (f_{18}), four functions (f_{15}, f_{20}, f_{22}, and f_{23}), fifth best in one function (f_{16}), and the sixth best in one function (f_{17}). Fortunately, the efficacy difference between ISA and the best performer in these functions is narrow. Moreover, the efficacy difference between the best and worst performers in all these fixed dimension multimodal functions is narrow.

TABLE V
APPRAISAL RESULT ON HANDLING TEN FIXED DIMENSION MULTIMODAL FUNCTIONS

F	Parameter	GSO [25]	LEO [18]	WaOA [19]	LOA [20]	TIA [24]	ISA
14	average score	2.9898x10^{1}	6.9641	9.1378	1.1281x10^{1}	9.7097	9.0318
	standard-dev	6.9495x10^{1}	3.7532	3.2881	4.1596	3.7622	3.8943
	position	6	1	3	5	4	2
15	average score	0.0387	0.0023	0.0011	0.0275	0.0032	0.0036
	standard-dev	0.0351	0.0042	0.0006	0.0263	0.0064	0.0078
	position	6	2	1	5	3	4
16	average score	-0.0753	-1.0306	-1.0293	-1.0019	-1.0154	-0.9725
	standard-dev	2.3231	0.0022	0.0066	0.0437	0.0361	0.1545
	position	6	1	2	4	3	5
17	average score	1.1719	0.3987	0.4015	0.4535	1.6252	2.4584
	standard-dev	1.9176	0.0008	0.0081	0.0935	2.1420	4.8160
	position	4	1	2	3	5	6
18	average score	7.9640x10^{1}	3.0092	3.3824x10^{1}	1.0279x10^{1}	2.3190x10^{1}	1.3070x10^{1}
	standard-dev	1.9065x10^{2}	0.0228	3.2724x10^{1}	1.8016x10^{1}	2.5467x10^{1}	1.7357x10^{1}
	position	6	1	5	2	4	3
19	average score	-0.0153	-0.0495	-0.0495	-0.0495	-0.0495	-0.0495
	standard-dev	0.0158	0.0000	0.0000	0.0000	0.0000	0.0000
	position	6	1	1	1	1	1
20	average score	-2.2830	-3.1647	-3.0378	-2.7059	-2.2291	-2.4646
	standard-dev	0.5551	0.1170	0.1565	0.3067	0.6244	0.4637
	position	5	1	2	3	6	4
21	average score	-1.2092	-3.1686	-2.9257	-2.1483	-2.3746	-2.9309
	standard-dev	0.7964	1.3330	1.5897	1.4563	1.6621	1.6043
	position	6	1	3	5	4	2
22	average score	-2.2948	-3.6288	-3.2669	-2.9516	-3.1676	-3.0526
	standard-dev	2.3532	1.2198	1.6775	1.7893	1.9866	1.1962
	position	6	1	2	5	3	4
23	average score	-2.1239	-3.1595	-3.1332	-2.9003	-2.0653	-2.4918
	standard-dev	1.8853	1.5384	1.7209	1.2490	0.8164	1.0600
	position	5	1	2	3	6	4

TABLE VI
SUPREMACY SUMMARY BASED ON GROUP OF FUNCTIONS

Cluster	GSO [25]	LEO [18]	WaOA [19]	LOA [20]	TIA [24]
1	7	5	5	7	4
2	5	4	3	5	5
3	9	0	3	4	5
Total	21	9	11	16	14

TABLE VII
SENSITIVITY ANALYSIS FOR DIFFERENT MAXIMUM ITERATION

Function	Average Fitness Score		Improve Significantly
	t_{max} = 25	t_{max} = 50	
1	0.0000	0.0000	no
2	0.0000	0.0000	no
3	0.6367	0.0000	yes
4	0.0000	0.0000	no
5	3.8938x10^{1}	3.8939x10^{1}	no
6	8.2229	8.3218	no
7	0.0120	0.0081	no
8	-3.1501x10^{3}	-3.1759x10^{3}	no
9	0.0000	0.0000	no
10	0.0000	0.0000	no
11	0.0020	0.0014	no
12	1.0240	0.9564	no
13	3.0912	3.0598	no
14	7.5890	8.7165	no
15	0.0131	0.0020	yes
16	-1.0191	-0.9927	no
17	1.4261	1.0494	no
18	1.1734x10^{1}	1.2757x10^{1}	no
19	-0.0495	-0.0495	no
20	-2.4677	-2.1700	no
21	-2.4616	-4.1761	no
22	-3.0320	-4.0506	no
23	-2.6332	-3.2767	no

Table 6 indicates the mix superiority compared to its contenders. Overall, ISA is better than GSO, LEO, WaOA, LOA, and TIA in 21, 9, 11, 16, and 14 functions respectively. It shows that ISA is superior to GSO, LOA, and TIA. The efficacy of ISA is equal compared to WaOA as ISA is better than WaOA in 11 functions and achieves the same result in two functions. Meanwhile, ISA is slightly inferior to LEO as it is better than LEO in only nine functions.

Still in the first appraisal, the sensitivity analysis is performed to evaluate the efficacy of ISA as the adjusted parameters change. In this analysis, there are two parameters that are evaluated: the maximum iteration and swarm size. The first analysis compares the efficacy for two different values of maximum iteration: 25 and 50. The result is provided in Table 7. The second analysis compares the efficacy for two different values of swarm size: 10 and 20. The result is provided in Table 8.

TABLE VIII
SENSITIVITY ANALYSIS FOR DIFFERENT SWARM SIZE

Function	Average Fitness Score		Improve Significantly
	$n(A)$ = 10	$n(A)$ = 20	
1	0.0000	0.0000	no
2	0.0000	0.0000	no
3	1.6690	0.2733	yes
4	0.0002	0.0000	no
5	3.8913x10^{1}	3.8907x10^{1}	no
6	7.9739	7.2339	no
7	0.0089	0.0051	no
8	-3.2803x10^{3}	-3.7678x10^{3}	no
9	0.0000	0.0000	no
10	0.0000	0.0000	no
11	0.0000	0.0013	no
12	0.8970	0.7260	no
13	3.0840	3.0718	no
14	6.5753	4.4964	no
15	0.0026	0.0003	yes
16	-1.0309	-1.0315	no
17	0.4107	0.3988	no
18	6.5589	3.0001	yes
19	-0.0495	-0.0495	no
20	-2.6857	-2.9573	no
21	-3.8830	-5.6371	no
22	-3.2682	-5.6600	no
23	-4.0471	-5.0429	no

Table 7 indicates that convergence has been achieved in the low maximum iteration. There is not any significant difference or improvement between 25 and 50 of maximum iteration in almost all functions except f_3 and f_{15}. In seven functions (f_1, f_2, f_4, f_9, f_{10}, f_{13}, and f_{16}), the stagnation occurs because the global optimal solution has been achieved or the final solution is near the global optimal solution.

Table 8 indicates that convergence has been achieved in the low swarm size. Like Table 10, there is not any significant difference or improvement between 10 and 20 of swarm size in almost all functions except in three functions (f_3, f_{15}, and f_{18}). Like Table 7, the stagnation occurs because the global optimal solution has been achieved or the final solution is near the global optimal solution in seven functions (f_1, f_2, f_4, f_9, f_{10}, f_{16}, and f_{17}).

TABLE IX
POWER RANGE OF TEN GENERATORS

Generator	Min Power (MW)	Max Power (MW)
1	10	55
2	20	80
3	47	120
4	20	130
5	50	160
6	70	240
7	60	300
8	70	340
9	135	470
10	150	470

In the second appraisal, ISA is challenged to overcome ELD problem in the grid system that comprises ten generators. The specification of each generator, including the quadratic constants and power range refers to [2] where the power range of each generator is given in Table 9 while the constants of the cost functions is given in Table 10. Based on Table 9, the minimum total power is 632 MW while the maximum total power is 2,365 MW. There are three total power demand scenarios including 1,000 MW, 1,500 MW, and 2,000 MW. The result is given in Table 11 to Table 13 for 1,000 MW, 1,500 MW, and 2,000 MW power demand consecutively.

TABLE X
CONSTANTS FOR COST FUNCTIONS

Generator	α	β	γ
1	0.12951	40.5407	1000.403
2	0.10908	39.5804	950.606
3	0.12511	36.5104	900.705
4	0.12111	39.5104	800.705
5	0.15247	38.5390	756.799
6	0.10587	46.1592	451.325
7	0.03546	38.3055	1243.531
8	0.02803	40.3965	1049.998
9	0.02111	36.3278	1658.569
10	0.01799	38.2704	1658.569

TABLE XI
APPRAISAL RESULT ON HANDLING ECONOMIC LOAD DISPATCH PROBLEM WITH 10 GENERATORS WITH 1,000 MW POWER DEMAND

No	Metaheuristic	Total Fuel Cost (USD/hour)		
		Average	Min	Max
1	GSO [25]	53,758	53,726	53,860
2	LEO [18]	53,791	53,751	53,895
3	WaOA [19]	53,767	53,739	53,798
4	LOA [20]	53,830	53,756	53,931
5	TIA [24]	53,774	53,731	53,814
6	ISA	53,784	53,731	53,850

TABLE XII
APPRAISAL RESULT ON HANDLING ECONOMIC LOAD DISPATCH PROBLEM WITH 10 GENERATORS WITH 1,500 MW POWER DEMAND

No	Metaheuristic	Total Fuel Cost (USD/hour)		
		Average	Min	Max
1	GSO [25]	79,070	78,577	80,378
2	LEO [18]	78,718	78,641	78,813
3	WaOA [19]	78,625	78,578	78,707
4	LOA [20]	78,886	78,665	79,277
5	TIA [24]	78,662	78,550	79,009
6	ISA	78,712	78,606	78,820

TABLE XIII
APPRAISAL RESULT ON HANDLING ECONOMIC LOAD DISPATCH PROBLEM WITH 10 GENERATORS WITH 2,000 MW POWER DEMAND

No	Metaheuristic	Total Fuel Cost (USD/hour)		
		Average	Min	Max
1	GSO [25]	107,795	106,544	109,157
2	LEO [18]	106,235	106,084	106,485
3	WaOA [19]	106,172	105,991	106,488
4	LOA [20]	106,829	106,365	107,553
5	TIA [24]	106,325	106,076	106,956
6	ISA	106,227	106,041	106,489

Table 11 to Table 13 indicates the fierce competition among metaheuristics in solving this ELD problem. In the 1,000 MW power demand scenario, ISA becomes the third-best performer while WaOA becomes the best performer. The range in this scenario is 133 USD/hour. In the 1,500 MW scenario, ISA becomes the fourth-best performer while WaOA becomes the best performer. In this scenario, the range is 1,671 USD/hour. In the 2,000 MW power demand scenario, the range of the average value of total fuel cost between the best performer and the worst performer is only 1,623 USD/hour. In this scenario, ISA becomes the third-best performer where LEO becomes the first best performer.

IV. DISCUSSION

In general, the appraisal result indicates the acceptable efficacy of the proposed ISA. The result shows that ISA is competitive during the appraisal using both theoretical and practical problems. ISA is competitive in solving the set of 23 functions where it is superior to GSO, LOA, and TIA, equal to WaOA, and slightly inferior to LEO. Based on the group perspective, in general, ISA is superior in solving high dimension problems while its efficacy is not superior in solving fixed dimension problems. ISA is also proven in achieving convergence in the low maximum iteration and swarm size in most of 23 functions.

ISA is still competitive in functions where it does not become the best performer by maintaining a narrow difference with the best performer. Meanwhile, ISA is competitive in solving ELD problem with a very narrow difference with the best one.

The mixed result in both appraisals highlights the NFL theory. The wide efficacy difference between the best and worst performers occurs in all high dimension functions except the f_8. Meanwhile, the narrow efficacy difference between the best and worst performers takes place in all fixed dimension multimodal functions and ELD problem. The wide efficacy difference indicates the space for improvement is highly probable. On the other hand, narrow efficacy difference indicates that the improvement is difficult for new optimization method, especially in ELD problem where the range is less than two percent.

The computational complexity ISA can be split between the initialization and iteration phases. During the initialization phase, the complexity is given as $O(n(E).d)$. It means that the complexity is linear to the swarm size or the dimension. On the other hand, during the iteration phase, the complexity is given as $O(2t_{max}.n(E).d)$. This presentation means that the complexity is linear to the maximum iteration, swarm size, or dimension during the iteration phase. Term 2 represents the two serial guided searches performed by every swarm member during the iteration.

Practically, there are various cases of ELD problems that can be employed in future studies. A few cases comprise all thermal generating units while a few other cases comprise both thermal generating units and renewable energy-based generating units, whether they are solar, wind, ocean wave, and so on [27]. The case employed in this paper comprises single power demand only. Meanwhile, there are a few cases where there are several cases regarding the power demand. A few derivatives contain multiple power demands with sequential time frame. In this case, ramp rate is initiated so that the power provided by each generating unit is not limited only by the minimum and maximum power but also the ramp rate. This ramp rate is initiated to avoid the power of a generating unit does not jump or falling too far [3] which may cause damage.

In a few cases, the environmental aspect is also considered. In this circumstance, the objective is transformed from the single objective problem into multi-objective problem. Besides minimizing the fuel cost, another objective is minimizing the pollutant treatment cost [28], minimizing power loss [29], and so on. Moreover, various cases can be implemented to this problem, such as IEEE 30, 57, 117 bus systems [30] and so on.

There are also two popular grid systems in Indonesia. The first grid system is the Java-Bali grid system while the second one is the South Sulawesi grid system. The Java-Bali grid system comprises of eight generating units where six of them are thermal units and two of them are hydroelectric units [3]. Meanwhile, the South Sulawesi grid system comprises of 15 generating units which are distributed through 57 transmission lines [31].

V. CONCLUSION

This paper has demonstrated a new metaheuristic called as iteration shift algorithm (ISA) and its implementation to overcome ELD problem. The presentation of ISA through conceptual description and its formalization through pseudocode and mathematical formulation has been conducted. The appraisal to evaluate its efficacy has been conducted by using both theoretical and practical problems. Overall, the result shows that the efficacy of ISA is acceptable in finding the quasi-optimal solution to these problems. Moreover, the appraisal result indicates the competitiveness of ISA among its contenders. ISA is better than its contenders (GSO, LEO, WaOA, LOA, and TIA) in 21, 9, 11, 16, and 14 functions out of 23 functions respectively. It means that ISA is superior to GSO, LOA, and TIA, equal to WaOA, and slightly inferior to LEO. Meanwhile, ISA is also competitive in solving ELD problem.

Future development based on this work can be conducted through several tracks. The improvement of ISA can be conducted by hybridizing it with other searches, such as local search, crossover, and so on. Improvement can also be taken by adding adaptive mechanisms when facing stagnation, for example by performing full random search, loosening the acceptance approach, and so on. In the context of ELD problem, ISA can be implemented to overcome various environments or by considering more parameters, such as ramp rate, loss, valve point, and so on.

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