Solving Economic Emission Dispatch Problem with Various Power Demand using New Metaheuristic Called Time-Shift Optimizer

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***Abstract*—Environmental issues become a major concern in many studies in engineering field, especially optimization. Meanwhile, many optimization studies utilize metaheuristics due to their flexibility. On the other hand, there are abundant metaheuristics available to employ. Unfortunately, studies that introduce a new metaheuristic and use environmental issues in their case are hard to find. This paper introduces a new swarm-based metaheuristic called time-shift optimizer (TSO). TSO employs a novel approach in constructing the reference based on the mixture of two agents: an exploration-oriented agent and exploitation-oriented agent. TSO is then challenged to handle both constrained and unconstrained problems. The set of 23 traditional functions is taken as the unconstrained problem while economic emission dispatch (EED) problem is taken as the constrained problem. EED problem is taken as a multi-objective problem that considers both economic and environmental aspects. In these assessments, TSO is confronted with preschool education optimization algorithm (PEOA), addax optimization algorithm (AOA), dollmaker optimization algorithm (DOA), golden search optimization (GSO), and slime mold algorithm (SMA). The result shows the supremacy of TSO in handling high dimension functions and competitive in handling fixed dimension functions and EED problems.**

***Index Terms*—environment, optimization, power system, economic emission dispatch, metaheuristic, swarm intelligence.**

I. Introduction

ENVIRONMENTAL isssues become a major concern in many studies, especially in the engineering field. Among them, carbon emission receives significant attention, such as in studies reducing the dissolved carbon emission in submerged vegetaion covered river network [1], investigating the carbon emission of civil aviation [2], analysing carbon emission in hospital [3], reducing carbon emission in logistic supply chain [4], optimizing train plan [5], and so on. Some studies investigates the renewable energies, such as studies in solar thermal poer plants [6], wind-solar enenergy storage [7], micro hydro [8], and so on.

Economic emission dispatch (EED) problem is one optimization problem in engineering, especially in power system that promotes the environmental issues equal with the economic issues. EED problem is a multi-objective problem whose objective is minimizing both fuel/operational cost and emission reduction cost [9]. EED is a derivative of economic load dispatch (ELD) problem which is a single objective problem where the objective is minimizing the operation or fuel cost only. Metaheuristics have been widely used in these studies, such as chaotic artificial hummingbird algorithm [10], simulated annealing [9], manta ray foraging optimization algorithm [11], artificial bee colony [12], chaotic driving training-based optimization [13], and so on. Unfortunately, studies in EED or ELD problems that also introduced new metaheuristics are hard to find.

There are abundant metaheuristics already exist in the recent decades. Specifically, there are abundant metaheuristics were introduced in recent years. Many of these metaheuristics are metaphor-based metaheuristics which are inspired by the behavior of animals, such as addax optimization algorithm (AOA) [14], prairie dog optimization algorithm (PDOA) [15], crayfish optimization algorithm (COA) [16], elk herd optimizer (EHO) [17], chameleon swarm algorithm (CSA) [18], apiary organizational based optimization algorithm (AOOA) [19], marine predator algorithm (MPA) [20], giant armadillo optimization (GAO) [21], and so on. Meanwhile, there are metaphor-based metaheuristics that imitates the social behavior, such as preschool education optimization algorithm (PEOA) [22], migration algorithm (MA) [23], language education optimization (LEO) [24], driving training based optimization (DTBO) [25], chef based optimization algorithm (CBOA) [26], election based optimization algorithm (EBOA) [27], dollmaker optimization algorithm (DOA) [28], mother optimization algorithm (MOA) [29], deep sleep optimizer (DSO) [30], modified social forces algorithm (MFSA) [31], and so on. Fortunately, there are also new metaheuristics that do not use metaphors and utilize their fundamental concept for their name, such as average subtraction-based optimization (ASBO) [32], subtraction-average based optimization (SABO) [33], total interaction algorithm (TIA) [34], average subtraction-based optimization (ASBO) [32], fully informed search algorithm (FISA) [35], golden search optimization (GSO) [36], group better-worse algorithm (GBWA) [37], and so on.

Despites the massive development of new metaheuristics, environmental issues have not been considered yet. Many of these studies employed standard sets of functions to investigate the performance of the proposed metaheuristics,

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such as 23 traditional functions, such as in TIA [34] or GSO [36]; or CEC series like in EHO [17]. Meanwhile, some studies employed standard mechanical design problems representing the constrained problems like in SABO [33], AOA [14], and so on. Once again, environmental issues are still not popular.

This paper is aimed at constructing a new metaheuristic called time shift optimizer (TSO). As the name suggests, this metaheuristic introduces a new approach in constructing a reference for the directed search by shifting the exploration to exploitation as the iteration goes. TSO does not utilize any metaphor so that its novel approach can be easily acknowledged.

This TSO is then assessed by employing it to handle both constrained and unconstrained problems. The set of 23 traditional functions is taken representing the unconstrained problem as this set of functions has been widely used in various studies promoting new metaheuristics. The EED problem with the case is Java-Bali power grid in Indonesia to promote the environmental issues rather than economic issues only.

Based on this previous explanation, below is the summary of novelties and scientific contributions of this paper.

1) This paper introduces a new metaheuristic called as time shift optimizer (TSO) whose novelty is on constructing the reference based on the shifting from exploration-oriented agent to exploitation-oriented agent during the iteration.
2) The assessment of the performance of TSO is conducted by employing it to handle both constrained and unconstrained problems. The standard set of 23 traditional functions exposes the unconstrained problem while two EED problems with multiple power demands represent the constrained problem.
3) TSO is confronted with five brand new swarm-based metaheuristics, including PEOA, AOA, DOA, GSO, and SMA during the assessment.

The organization of the rest of this paper is as follows. Section two exposes the model of the proposed TSO including the concept, pseudocode, and mathematical formulation. Section three provides the model of economic emission dispatch problem including the concept and mathematical formulation. Section four provides the assessment, including the scenario and result. Section five provides a comprehensive discussion regarding the result, finding, complexity, limitation, and baseline for future studies. Section six provides the summary of the conclusion and tracks for future studies.

II. The Proposed Model

The time-shift optimizer (TSO) is constructed based on the concept of the transition of shifting in constructing a reference which is controlled by the iteration. This transition reflects the orientation change during the time. Rather than changing strategy in extreme way like in MPA, TSO employs smooth transition by changing the portion of components that construct the reference. In this context, this transition is performed in a deterministic manner. There are two guided searches that are employed during the iteration. There is a specific reference in every search.

The reference is constructed based on the mixture of two agents. The first agent is the exploration-oriented agent while the second agent is the exploitation-oriented agent. The portion of the exploration-oriented agent decreases linearly during the iteration while the portion of the exploitation-oriented agent increases linearly during the iteration. This concept reflects the linear shifting from exploration to exploitation during the iteration. This shifting is illustrated in Fig. 1.

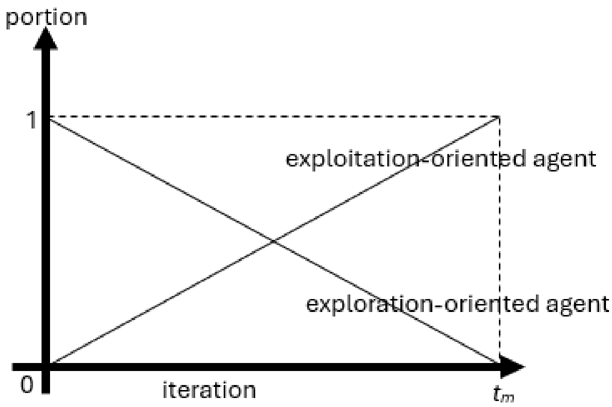

Fig. 1 Shifting portion of the agents that construct the reference during the iteration.

In the first search, the reference is the mixture between a randomly picked higher quality member and the highest quality member. In this first search, the randomly picked higher quality member represents the exploration-oriented agent while the highest quality member represents the exploitation-oriented agent. This first search, the motion is toward the reference.

In the second search, the reference is the mixture of a randomly picked member within the swarm and a randomly picked higher quality member. In this second search, the randomly picked member within swarm represents the exploration-oriented agent while the randomly picked higher quality member represents the exploitation-oriented agent.

In this second search, the direction of the motion depends on the comparative quality of the reference related to the member. If the reference is better than the member then the member moves toward its reference. Otherwise, the member moves away from its reference.

TABLE I
ANNOTATIONS FOR THE MODEL OF TSO

Not.	Description
b_l, b_u	lower and upper boundaries
c_1, c_2	first and second candidates
f	objective function
i, j	indexes for swarm members and dimensions
r_1, r_2	first and second references
s	swarm member
S	swarm
s_{hst}	highest quality member
S_{hgr}	a set that consists of higher quality members
s_{s1}, s_{s2}	the first and second randomly picked member
t	iteration
t_m	maximum iteration
u_1	uniform random [0,1]
u_2	uniform random among a population

The formal description of the model of TSO is provided in algorithm 1 while the formulation following the model is provided using (1) to (7). The annotations used in this model and mathematical formulations are provided in Table 1.

algorithm 1: time shift optimizer
1 begin
2 for all $s \in S$
3 initialize s_i
4 update s_{hst}
5 end for
6 for t = 1 to t_m
7 for all $s \in S$
8 first motion of s_i
9 update s_{hst}
10 second motion of s_i
11 update s_{hst}
12 end for
13 end for
14 return s_{hst}
15 end

Below is the explanation of algorithm 1. As is common in metaheuristics, the algorithm is split into two stages. The first stage is initialization while the second stage is iteration. Initialization is employed to generate the initial value or position of each swarm member where in algorithm 1 is provided from line 2 to line 5. Iteration is employed to improve the quality of solution based on stochastic motions where in this algorithm is provided from line 6 to 13. Then the highest quality member becomes the final solution, and this value is returned to the main program.

There are two processes performed in the initialization stage. The first process is generating the initial value of each swarm member which is uniformly distributed along the space as stated in (1). This process gives equal opportunity along the space as there is not any initial clue regarding the location of the global optimal solution. The second process is the updating of the highest quality member which is formalized using (2).

$$s_{i,j} = b_{l,j} + u_1\left(b_{u,j} - b_{l,j}\right) \tag{1}$$

$$s'_{hst} = \begin{cases} s_i, f(s_i) < f(s_{hst}) \\ s_{hst}, else \end{cases} \tag{2}$$

As provided in algorithm 1, there are two motions performed by each swarm member during the iteration. Each motion will be followed by the updating of the highest quality member as provided in line 9 and line 11. This process is conducted as the highest quality member is used to construct the reference whether in the first and the second motions.

The formalization of the first motion is provided using (3) to (7). Equation (3) formalizes the construction of a pool consisting of all higher quality members relative to the related member plus the highest quality member. Equation (4) formalizes the uniform random picking of a member within this pool. Equation (5) exposes the mixture of a randomly picked higher quality member and the highest quality member to create the first reference. Equation (6) formalizes the motion toward the first reference. Equation (7) formalizes the updating of the swarm member based on the first candidate.

$$S_{hgr,i} = \{s \epsilon S \wedge f(s) < f(s_i)\} \cup s_{hst} \tag{3}$$

$$s_{s1,i} = u_2\left(S_{hgr,i}\right) \tag{4}$$

$$r_{1,i,j} = \left(1 - \frac{t}{t_m}\right) s_{s1,i,j} + \frac{t}{t_m} s_{hst,j} \tag{5}$$

$$c_{1,i,j} = s_{i,j} + u_1\left(r_{1,i,j} - 2s_{i,j}\right) \tag{6}$$

$$s'_i = \begin{cases} c_{1,i}, f\left(c_{1,i}\right) < f(s_i) \\ s_i, else \end{cases} \tag{7}$$

The formalization of the second motion is provided using (8) to (11). Equation (8) formalizes the randomly picking member within the swarm. Equation (9) formalizes the construction of second reference which is the mixture of the randomly picked higher quality member and a randomly picked member. Equation (10) formalizes the second motion with two possible directions. Equation (11) formalizes the updating process of the swarm member using the second candidate.

$$s_{s2,i} = u_2(S) \tag{8}$$

$$r_{2,i,j} = \left(1 - \frac{t}{t_m}\right) s_{s2,i,j} + \frac{t}{t_m} s_{s1,i,j} \tag{9}$$

$$c_{2,i,j} = \begin{cases} s_{i,j} + u_1\left(r_{2,i,j} - 2s_{i,j}\right), f\left(r_{2,i}\right) < f(s_i) \\ s_{i,j} + u_1\left(s_{i,j} - 2r_{2,i,j}\right), else \end{cases} \tag{10}$$

$$s'_i = \begin{cases} c_{2,i}, f\left(c_{2,i}\right) < f(s_i) \\ s_i, else \end{cases} \tag{11}$$

III. Economic Emission Dispatch Model

The general model of EED problem as an optimization problem can be split into three parts. The first part is the system. The second part is the objective function. The third part is the constraints which consists of the equality constraint and inequality constraint. The annotations used in this model are provided in Table 2.

TABLE II
ANNOTATIONS FOR THE EED PROBLEM

Not.	Description
g	Generating unit
G	Set of generating units
p	power
p_{min}, p_{max}	minimum and maximum powers
p_{total}	total power
p_{demand}	power demand
w_e, w_f	emission cost weight and fuel cost weight
c_e, c_f	emission cost and fuel cost
c_{etotal}	total emission cost
c_{ftotal}	total fuel cost
c_{total}	total cost
α, β, γ	constants of cost function
i	generating unit index

The system of EED problem is a set of generating units. These generating units are connected to provide power. This system is formalized using (12).

$$G = \{g_1, g_2, g_3, \dots, g_n\} \tag{12}$$

As is common in every system, there are constraints that limit the operation of the system. In EED, these constraints are split into the equality constraint and inequality constraint. The equality constraint of EED is that the total power provided by the system should meet the power demand as stated in (13) [38]. Meanwhile, the total power of the system is obtained by accumulating the power provided by every generating unit in the system as formalized in (14). Then, each generating unit can provide power within its range which may be different among generating units as stated in (15). This constraint represents the inequality constraint. In its basic form, the power loss and the ramp rate are not considered.

$$p_{total} = p_{demand} \tag{13}$$

$$p_{total} = \sum_{i=1}^{n} p_i \tag{14}$$

$$p_{min,i} \leq p_i \leq p_{max,i} \tag{15}$$

EED problem is a multi-objective problem. Its objective is minimizing the total cost which is formulated using (16). This total cost is constructed by adding the weighted total emission cost and weighted total fuel cost as formulated in (17) [9]. The total emission cost is obtained by accumulating the emission cost of all generating units as stated in (18) while the total fuel cost is obtained by accumulating the fuel cost of all generating units as stated in (19). The emission cost function and fuel cost of each generating unit is provided in quadratic equation as provided in (20) for the emission cost function and in (21) for the fuel cost function.

$$objective: \min\ (c_{total}) \tag{16}$$

$$c_{total} = w_e c_{etotal} + w_f c_{ftotal} \tag{17}$$

$$c_{etotal} = \sum_{i=1}^{n} c_{e,i} \tag{18}$$

$$c_{ftotal} = \sum_{i=1}^{n} c_{f,i} \tag{19}$$

$$c_{e,i} = \alpha_{e,i} + \beta_{e,i} p_i + \gamma_{e,i} p_i^2 \tag{20}$$

$$c_{f,i} = \alpha_{f,i} + \beta_{f,i} p_i + \gamma_{f,i} p_i^2 \tag{21}$$

IV. Assessment and Result

This section exposes the assessment of TSO to investigate the performance of TSO in handling optimization problems and the result. There are two assessments in this work. The first assessment is conducted to investigate the performance of TSO in handling standard unconstrained problems. The 23 traditional functions are taken as the standard unconstrained problem. The second assessment is conducted to investigate the performance of TSO in handling the practical constrained problem. The EED problem with the case of Java-Bali power grid system is taken as the constrained practical problem.

The 23 traditional functions are taken based on several reasons. First, these functions have been employed as standard functions in abundant studies introducing new metaheuristics, such as TIA [34], AOA [14], DOA [28], SMA [39], and so on. Second, these functions cover various considerations and scope as they can be split into seven high dimension unimodal functions (HDUs), six high dimension multimodal functions (HDMs), and ten fixed dimension multimodal functions (FDMs). The unimodal functions have only one optimal solution that represents the global optimal solution while the multimodal functions have multiple optimal solutions where only one of these optimal solutions is the global optimal one. The detailed specification of these 23 functions is provided in Table 3.

TABLE III
SPECIFICATION OF 23 TRADITIONAL FUNCTIONS

No	Function	Dim	Space	Target
1	Sphere	20	[-100, 100]	0
2	Schwefel 2.22	20	[-100, 100]	0
3	Schwefel 1.2	20	[-100, 100]	0
4	Schwefel 2.21	20	[-100, 100]	0
5	Rosenbrock	20	[-30, 30]	0
6	Step	20	[-100, 100]	0
7	Quartic	20	[-1.28, 1.28]	0
8	Schwefel	20	[-500, 500]	-418.9 x *dim*
9	Ratsrigin	20	[-5.12, 5.12]	0
10	Ackley	20	[-32, 32]	0
11	Griewank	20	[-600, 600]	0
12	Penalized	20	[-50, 50]	0
13	Penalized 2	20	[-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

In both assessments, the TSO is confronted with five new metaheuristics as its benchmarks. These confronters include PEOA, AOA, DOA, GSO, and SMA. In both assessments, the population is set to 5 while the maximum iteration is set to 10. The decimal point which is less than 10^{-4} is rounded down to 0.

The result of the first assessment is provided in Table 4 to Table 7. Table 4 exhibits the result in handling HDUs. Table 5 exhibits the result in handling HDMs. Table 6 exhibits the result in handling FDMs. Table 7 summarizes the supremacy of TSO relative to its confronters.

The result in Table 4 shows the supremacy of TSO in handling the HDUs. TSO becomes the first best in all seven HDUs. Meanwhile, there are also three other metaheuristics that become the first best too which are PEOA, DOA, and SMA. Table 4 also exposes the wide performance disparity between the best optimizer and the worst optimizer in handling HDUs. As these HDUs are designed to assess the exploitation capability [32], it can be said that TSO has superior exploitation capability compared to its confronters.

TABLE IV
ASSESSMENT RESULT IN HANDLING HDUS

Function	Parameters	PEOA	AOA	DOA	GSO	SMA	TSO
1	mean	1.7319×10^{1}	7.4623×10^{1}	8.0586×10^{1}	1.5645×10^{4}	3.4243×10^{3}	0.0000
	rank	2	3	4	6	5	1
2	mean	0.0000	0.0122	0.0000	6.1015×10^{25}	0.0000	0.0000
	rank	1	5	1	6	1	1
3	mean	1.1791×10^{3}	5.3763×10^{3}	3.0222×10^{3}	3.1239×10^{4}	1.5877×10^{4}	0.2288
	rank	2	4	3	6	5	1
4	mean	6.7436	8.1926	9.2871	5.4014×10^{1}	2.0272×10^{1}	0.0061
	rank	2	3	4	6	5	1
5	mean	4.7325×10^{2}	3.5715×10^{3}	7.6046×10^{3}	2.5322×10^{7}	4.6695×10^{6}	1.8941×10^{1}
	rank	2	3	4	6	5	1
6	mean	2.1384×10^{1}	8.2437×10^{1}	9.7779×10^{1}	1.4492×10^{4}	1.8463×10^{3}	3.8324
	rank	2	4	3	6	5	1
7	mean	0.0904	0.1027	0.1004	8.4436	5.8436×10^{1}	0.0216
	rank	2	4	3	5	6	1

TABLE V
ASSESSMENT RESULT IN HANDLING HDMS

Function	Parameters	PEOA	AOA	DOA	GSO	SMA	TSO
8	mean	-2.1482×10^{3}	-2.1017×10^{3}	-2.1036×10^{3}	-1.4324×10^{3}	-2.9449×10^{3}	-1.6156×10^{3}
	rank	2	4	3	6	1	5
9	mean	3.2251×10^{1}	1.0470×10^{2}	7.4954×10^{1}	1.8053×10^{2}	1.6813×10^{1}	0.0018
	rank	3	5	4	6	2	1
10	mean	1.9070	5.8460	4.5865	1.8074×10^{1}	7.4494	0.0016
	rank	2	4	3	6	5	1
11	mean	1.0359	1.8016	1.9568	1.4558×10^{2}	1.4621×10^{1}	0.0274
	rank	2	3	4	6	5	1
12	mean	1.6634	3.5461	3.4334	2.4417×10^{7}	6.0377×10^{6}	1.0490
	rank	2	4	3	6	5	1
13	mean	6.0108	4.6176×10^{1}	1.2267×10^{1}	6.8181×10^{7}	8.8517×10^{6}	3.1373
	rank	2	4	3	5	6	1

TABLE VI
ASSESSMENT RESULT IN HANDLING FDMS

Function	Parameters	PEOA	AOA	DOA	GSO	SMA	TSO
14	mean	1.0398×10^{1}	1.0826×10^{1}	1.1195×10^{1}	2.3833×10^{1}	1.1924×10^{1}	1.1353×10^{1}
	rank	2	1	3	6	5	4
15	mean	0.0110	0.0218	0.0226	0.0547	0.1448	0.0160
	rank	1	3	4	5	6	2
16	mean	-0.9780	-0.9741	-1.0004	-0.6690	1.0076	-0.9243
	rank	2	3	1	5	6	4
17	mean	2.1360	0.5108	0.4903	4.8609	3.4889	3.7604
	rank	3	2	1	6	4	5
18	mean	2.4773×10^{1}	1.9708×10^{1}	1.0256×10^{1}	2.1268×10^{1}	9.0660×10^{1}	2.2561×10^{1}
	rank	5	2	1	3	6	4
19	mean	-0.0495	-0.0495	-0.0495	-0.0044	-0.0495	-0.0495
	rank	1	1	1	6	1	1
20	mean	-2.5706	-2.7758	-2.9484	-2.1748	-0.5896	-1.5168
	rank	3	2	1	4	6	5
21	mean	-2.6305	-2.3994	-2.1242	-1.5660	-1.3453	-1.1093
	rank	1	2	3	4	5	6
22	mean	-3.0701	-1.8439	-1.9839	-2.1151	-1.8623	-1.3998
	rank	1	5	3	2	4	6
23	mean	-2.3108	-2.4478	-2.3388	-1.8349	-1.4991	-1.7481
	rank	3	1	2	4	6	5

Table 5 also exhibits the supremacy of TSO in handling HDMs. TSO becomes the first best in handling five HDMs (f_9 to f_{13}). Meanwhile, TSO becomes the fifth best in handling f_8 and it is better only than GSO. Fortunately, the performance disparity among metaheuristics in f_8 is narrow. It means that TSO is still competitive in this function. Meanwhile, the performance disparity between TSO as the best optimizer and the worst optimizer in five other HDMs is wide. This result indicates the supreme exploration capability of TSO as the high dimension multimodal functions are designed to investigate the exploration capability [32].

Result in Table 6 indicates that TSO is competitive in handling the FDMs. TSO becomes the first best only in one function (f_{19}), second best in one function (f_{15}), fourth best in three functions (f_{14}, f_{16}, and f_{18}), fifth best in three functions (f_{17}, f_{20} and f_{23}), and sixth best in two functions (f_{21} and f_{22}). Fortunately, the performance disparity among metaheuristics in almost all FDMs is narrow except in f_{15}. This result indicates the competitive performance of TSO in balancing its exploration and exploitation capabilities as FDMs are designed to investigate this capability [32].

TABLE VII
Supremacy Summary of TSO

Cluster	PEOA	AOA	DOA	GSO	SMA
1	6	7	6	7	6
2	5	5	5	6	5
3	1	1	1	5	6
Total	12	13	12	18	19

Summary in Table 7 exhibits the dominance of TSO in high dimension functions, whether they are unimodal functions or multimodal ones. Meanwhile, TSO is not superior in handling FDMs except compared to SMA. In general, TSO is superior to PEOA, AOA, DOA, GSO, and SMA in 12, 13, 12, 18, and 19 functions respectively.

The second assessment is performed by employing TSO and its five confronters to solve the EED problem. There are two cases taken in this second assessment. The Java-Bali power grid was taken as the first case. Java-Bali power grid and connectivity is the largest power grid in Indonesia as it serves the most populous and industrialized area in Indonesia. This circumstance makes this power grid critical to this country. The six-unit system is taken as the second case.

The Java-Bali power system consists of eight power plants. Six of them are thermal power plants so that it provides emission while the two others are hydro power plants which are more eco-friendly [9]. The specification of these power plants is provided in Table 8 to Table 10 [40]. Table 8 exposes the power range. Table 9 provides the data related to the constants of the fuel cost. Table 10 provides the data related to the emission cost.

In this first case of the second assessment, there are three power demands: 7,000 MW; 11,000 MW; and 15,000 MW. This demand exposes the demand which is near the minimum total power, middle total power demand, and maximum power demand. The result is provided in Tables 11 to 13.

TABLE VIII
Power Range of 8-Unit System

g	p_{min} (MW)	p_{max} (MW)
1	1,610	4,200
2	934	2,308
3	404	1,008
4	208	700
5	848	2,400
6	1,080	4,714
7	360	900
8	305	1,610

TABLE IX
Fuel Cost Related Constants of 8-Unit System

g	$\alpha_{f,i}$	$\beta_{f,i}$	$\gamma_{f,i}$
1	57,543,208.0	3,332,794.0	-400.0
2	519,353,767.1	3,047,098.0	691.0
3	0.0	400.0	0.0
4	0.0	660.0	0.0
5	133,177,025.6	2,828,349.0	-80.0
6	180,205,527.9	2,104,640.0	218.0
7	140,621,312.5	2,545,832.0	203.0
8	112,522,922.1	5,877,235.0	-73.0

TABLE X
Emission Cost Related Constants of 8-Unit System

g	$\alpha_{e,i}$	$\beta_{e,i}$	$\gamma_{e,i}$
1	34,251,909.8	1,983,806.2	-236.7
2	72,202,664.7	423.6	96.2
3	0.0	0.0	0.0
4	0.0	0.0	0.0
5	93,654,729.7	1,988,993.9	-56.9
6	123,428,443.8	1,441,534.9	149.5
7	140,621,312.5	2,545,832.5	62.1
8	24,146,549.8	1,261,209.3	-15.8

TABLE XI
Assessment Result with 7,000 MW Power Demand

No	Optimizer	Total Cost (rupiah/hour)
1	PEOA	12,800,620,703
2	AOA	13,074,232,813
3	DOA	12,986,151,634
4	GSO	13,787,688,076
5	SMA	13,064,359,854
6	TSO	13,576,341,541

TABLE XII
Assessment Result with 11,000 MW Power Demand

No	Optimizer	Total Cost (rupiah/hour)
1	PEOA	18,319,300,447
2	AOA	18,252,351,240
3	DOA	18,178,744,481
4	GSO	20,217,077,846
5	SMA	18,527,378,607
6	TSO	19,551,756,536

TABLE XIII
Assessment Result with 13,000 MW Power Demand

No	Optimizer	Total Cost (rupiah/hour)
1	PEOA	28,728,138,239
2	AOA	28,822,632,124
3	DOA	28,721,085,465
4	GSO	29,285,572,248
5	SMA	28,745,702,931
6	TSO	29,144,245,323

The 6-unit system consists of six generating units. The detailed specification is provided in Table 14 to Table 16 [41]. There are three power demands: 500 MW, 800 MW, and 1100 MW. The result is provided in Table 17 to Table 19.

TABLE XIV
Power Range of 6-Unit System

g	p_{min} (MW)	p_{max} (MW)
1	10	125
2	10	150
3	35	210
4	35	225
5	125	325
6	130	325

TABLE XV
Fuel Cost Related Constants of 6-Unit System

g	$\alpha_{f,i}$	$\beta_{f,i}$	$\gamma_{f,i}$
1	756.7988	38.5390	0.1524
2	451.3251	46.1591	0.1058
3	1243.5311	38.3055	0.0354
4	1049.9977	40.3965	0.0280
5	1356.6592	38.2704	0.0179
6	1658.5696	36.3278	0.0211

TABLE XVI
Emission Cost Related Constants of 6-Unit System

g	$\alpha_{e,i}$	$\beta_{e,i}$	$\gamma_{e,i}$
1	13.8593	0.3276	0.0041
2	13.8593	0.3276	0.0041
3	40.2669	-0.5455	0.0006
4	40.2669	-0.5455	0.0006
5	42.8955	-0.5111	0.0046
6	42.8955	-0.5111	0.0046

TABLE XVII
Assessment Result with 500 MW Power Demand

No	Optimizer	Total Cost (USD/hour)
1	PEOA	13,626
2	AOA	13,608
3	DOA	13,607
4	GSO	13,621
5	SMA	13,613
6	TSO	13,658

TABLE XVIII
Assessment Result with 800 MW Power Demand

No	Optimizer	Total Cost (USD/hour)
1	PEOA	20,583
2	AOA	20,549
3	DOA	20,557
4	GSO	20,608
5	SMA	20,557
6	TSO	20,728

TABLE XIX
Assessment Result with 1,100 MW Power Demand

No	Optimizer	Total Cost (USD/hour)
1	PEOA	28,121
2	AOA	28,065
3	DOA	28,061
4	GSO	28,368
5	SMA	28,904
6	TSO	28,503

The result indicates that competition among metaheuristics in handling the EED problem is fierce. This circumstance occurs in both cases. The ratio between the ranges compared to the average total cost is very narrow. In the first case, TSO becomes the fifth best in all three scenarios while GSO becomes the worst. In the second case, TSO becomes the worst optimizer while the best optimizer while DOA becomes the best optimizer in 500 MW and 1,100 MW power demand while AOA becomes the best optimizer in 800 MW power demand.

V. DISCUSSION

Overall, the assessment result shows that the performance of TSO is acceptable. TSO has superior exploration and exploitation capabilities as it can manage the high dimension functions compared to its confronters. In these functions, TSO is better than PEOA [22], AOA [14], and DOA [28] that are enriched with the neighborhood search. TSO is also better than GSO [36] and SMA [39] that do not employ stringent acceptance role. This superior performance also proves that the concept of TSO in mixing the exploration-oriented agent and exploitation-oriented agent is proven to work.

The performance disparity among cases also exposes and strengthens the no-free-lunch (NFL) theory. As it is known, the performance of any optimization technique highly depends on the problem it tries to handle and not just based on its nature. It makes a technique can be superior in handling some problems and poor or mediocre in other problems [21]. The assessment result exhibits the supremacy of TSO in handling the high dimension functions whether they are the unimodal or multimodal ones. Meanwhile, TSO is still competitive but not superior in handling the fixed dimension multimodal functions and EED problem. The assessment result also exposes the wide performance disparity between the best and worst optimizers in all high dimension unimodal functions and most of high dimension multimodal functions. Meanwhile, this performance disparity is narrow in most of fixed dimension multimodal functions. This performance disparity becomes narrower in all three scenarios in EED problem.

The computational complexity of TSO is highly related to the number of loops it employs. During the initialization, the complexity can be formulated as $O(n(S).d)$. Meanwhile, the complexity during the iteration can be formulated as $O(t_m.n(S)2.d)$.

Despite its effectiveness through shifting exploration to exploitation as iteration goes, there are a lot of other techniques that can be explored. This circumstance can be seen as a limitation and potential for future studies. This circumstance can be seen as limitation because this single metaheuristic can accommodate only single shifting strategy. On the other hand, this circumstance can be seen as potential because it makes opportunity to employ other shifting strategies for future new metaheuristics. TSO employs a linear shifting strategy. On the other hand, there are another trend, such as quadratic, exponential, logarithmic, or sinusoidal. On the other hand, the shifting can be employed by accommodating the acceptance strategy where in the beginning, the metaheuristic is flexible enough to accommodate worse solution candidate while in the later iteration, the worse solution candidate is much harder to be tolerated.

Another mechanism in shifting exploration to exploitation can be conducted by reducing the solution space. This reduction can be achieved in many ways. The most common method is reducing the area for local or neighborhood search. Meanwhile, some other options can be taken, such as marking certain regions where they have been visited but fail to provide improvement, focusing on more specific regions, and so on.

There are abundant optimization problems that can be employed as cases for investigation. In the power system, the problems include economic load dispatch problem, unit commitment problem, flower flow problem, and so on. Some other parameters can also be included such as ramp rate, power loss, and so on. Moreover, future studies can be performed through investigating more new use cases, especially the local ones rather than common or classic use cases.

There are also abundant optimization problems in the supply chain from production, warehousing, to shipping. All these problems can be numerical or combinatorial. In the production system, optimization spans from allocation problem, which is allocating certain number of tasks or jobs into certain number of limited resources, which are machines, people, and so on; vendor or supplier selection, raw materials purchasing problem, and so on. In transportation sector, there are several new practical optimization problems, such as passenger and freight co-transportation problem [42], vehicle scheduling for refined oil product [43], collaborative system between urban rail passenger and freight [44], and so on.

Moreover, the future studies can also be conducted by confronting TSO with a lot of new metaheuristics. These new metaheuristics can be the branded new ones or the modified versions of older metaheuristics. This assessment is important to investigate the superiority or competitiveness of TSO compared with new metaheuristics.

VI. CONCLUSION

This paper has provided the construction of new a novel metaheuristic called time-shift optimizer (TSO). This presentation includes the fundamental concept, formalization, and the assessment to investigate its performance. Through the assessment, it is proven the supremacy of TSO compared to its confronters in handling the standard unconstrained problem where the set of 23 traditional functions is taken as the case. In this assessment, TSO is superior to PEOA, AOA, DOA, GSO, and SMA in 12, 13, 12, 18, and 19 functions out of 23 functions. Its supremacy comes mainly from the high dimension functions from where it proves the supreme exploration and exploitation capabilities of TSO. The assessment result also proves the competitiveness of TSO in handling the constrained multi-objective problem where EED problem is taken, and the use-case is the Java-Bali power grid system.

In the future, more assessments in handling various constrained practical problems are needed. These problems can be numerical problems or combinatorial problems. Moreover, the basic form of TSO is still open for improvement or hybridization.

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