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Performance of Turbulent Flow of Water Optimization on Economic Load Dispatch Problem

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ABSTRACT The economic load dispatch (ELD) problems considering nonlinear characteristics where an optimal combination of power generating units is selected in order to minimize the total cost by economic allocation of power produced and the emission cost. As a consequence, optimal allocation is performed by considering both fuel cost and emission leading to Combined Economic and Emission Dispatch (CEED). This study presents a new Meta-heuristic algorithms (MHs) called the Turbulent Flow of Water Optimization (TFWO), which is based on the behaviour of whirlpools created in turbulent water flow, for solving different variants of ELD and CEED. To verify the robustness of the TFWO, various test network of CEED with effect of valve, and ELD with losses of transmission are incorporated. In comparison with seven well-known MHs such as Cuckoo Search Algorithm (CSA), Grey Wolf Algorithm (GW), Sine Cosine Algorithm (SCA), Earth Worm Optimization Algorithm (EWA), Tunicate Swarm Algorithm (TSA), Moth Search Algorithm (MSA) and Teaching Learning Based Optimization (TLBO), the TFWO provides the minimum fuel cost and significantly robust solutions of ELD problem over all tested networks. The results confirm the potential and effectiveness of the GWO to be a promising technique to solve various ELD problems.

INDEX TERMS Turbulent flow of water optimization (TFWO), economic load dispatch (ELD), combined economic and emission dispatch (CEED), metaheuristic optimization algorithms.

ABBREVIATIONS

ACO	Ant Colony Optimization
CEED	Economic and Emission Dispatch
PSO	Particle Swarm Optimization
WOA	Whale Optimization Algorithm
IGWO	Improved Grey Wolf Optimization
DE	Differential evolution
EWA	Earthworm optimization algorithm
BA	Bat Algorithm
CTO	Class Topper Optimization
ACS	Artificial Cooperative Search
WMA	Woodpecker Mating Algorithm
SSA	Salp Swarm Algorithm
SCA	Sine Cosine Algorithm
TLBO	Teaching Learning Based Optimization
ELD	Economic Load Dispatch
CSA	Crow Search Algorithm
FA	Firefly Algorithm
MFO	Moth Flame Optimizer
HS	Harmony Search
TSA	Tree Seed Algorithm
TFWO	Turbulent Flow of Water Optimization

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I. INTRODUCTION

The complexity of power system operation and planning is increasing day by day. Economic Load Dispatch (ELD) is one such complex power system problems involving ELD involves reduction of the cost of production by economically allocating the power produced by each unit [1], [2]. In addition to reduction of production cost nowadays emphasis is laid on reduction of emission [3], [4]. As a consequence, optimal allocation is performed by considering both emission and cost leading to Combined Emission and Economic Dispatch (CEED). Various real-life applications are solved using Meta-heuristic Algorithms (MHs) [5]–[7]. For example, nature-inspired algorithms mimic the biological, physical, or environmental processes [8]. Furthermore, several MHs are performed relatively well on the ELD problem. For instance, cost-effective emission dispatch problems is solved using the improved Manta ray foraging optimizer [9], also, in [10], the Gradient-Based Optimizer (GBO) is applied to solve the ELD Problem. Despite the availability and use of different MHs for solving ELD, researchers are still proposing new and novel algorithms for its solution.

Economic Load Dispatch problem objective function is performed as a quadratic equation. based on that, there are two ways for analyzing the problem of ELD. The first way; the techniques of traditional mathematical such as Newton methods, Lagrangian multiplier method, Lambda iteration method, Dynamic programming and Gradient method [11]. The second way is the metaheiristics algorithms. This algorithms are used in several problems such as extraction of photovoltaic parameters using gradient based optimizer [12] and Turbulent flow of water optimization [13]. In addition, solving ELD problem is performed with several algorithms such as non dominated sorting genetic algorithm [14], modified jrill algorithm [15], Whale Optimization Algorithm [16], Henry gas solubility optimization [17], gravitational search algorithm [18], improved Firework Algorithm [19], grasshopper optimization algorithm [20], multi gradient practical swarm optimization [21], Salp Swarm Algorithm [22], Differential Evolution [23], Equilibrium Optimizer [24], reinforcement learning [25], virus colony search algorithm [26], Harmony Search Algorithm [27], improved grey wolf optimization [28], bat algorithm [29], improved class topper optimization algorithm [30], improved bat algorithm [31], Ant Colony Optimization [32], improved Jaya algorithm [33] and artificial cooperative search algorithm [34].

In [14], authors have discussed the constraint handling techniques by multi-objective evolutionary algorithms in case of ELD and CEED. In [15], modified krill algorithm is used for solving constrained ELD. In [16], the authors have applied WOA to solve static as well as dynamic ELD problem. In [17], the authors used WMA to solve ELD. The simulation results confirmed the superior performance of WMA as compared to other MHs. In [18], the authors have proposed a novel memory-based GSA for solving ELD. The memory-based GSA performed better than the conventional GSA in solving ELD. In [19], the authors have solved dynamic ELD using an modified FA version in multi-area power systems. In [20], the authors have solved a ELD problem for a power system of hybrid wind-based using oppositional based chaotic grasshopper optimization algorithm. In [21], authors have solved real power limitations in the dynamic ELD of large-scale thermal power units under the effects of valve-point loading and ramp time constrains by multi-gradient PSO. In [22], the authors have formulated the dynamic ELD problem incorporating commercial EVs and used SSA to solve the problem. In [23], the authors have solved the multi-area ELD problem by DE. In [24], the authors have used a pareto based PSO for solving CEED. The proposed PSO performed better than NSGA II on CEED problem.

In [25], the authors have modelled the ELD problem in presence of EVs and solved the problem by reinforcement learning. In [26], the authors have solved the ELD problem in presence of wind energy resources and EVs by applying virus search algorithm. In [27], the authors have solved the ELD problem for a microgrid by Harmony Search Algorithm. In [28], authors have used IGWO for solving ELD and CEED. Simulation results indicated that IGWO performs better than GWO on ELD and CEED. In [29], the authors have used BA to solve continuous ELD with and without the effect of valve point. Also, the ELD application in a power system is solved using class topper optimization (CTO) algorithm in [30]. In [31], authors have used an improved version of BA to solve ELD in presence of renewable energy sources. In [32], authors have used ACO to solve ELD with losses. In [33], authors have proposed a multi-population-based Jaya algorithm to solve ELD. The simulated results established the superiority of multi-population-based Jaya algorithm over basic Jaya algorithm. In [34], authors have used ACS to solve ELD with losses. In [35], the authors have used Squirrel Search Algorithm to solve CEED for multi-area system. In [36], the authors have used an improved simplex based PSO for solving CEED. In [37], authors have modelled the ELD problem in presence of wind farms and flexible resources in a multi-objective framework and solved the problem by fuzzy logic. In [38], the authors have used MFO algorithm for solving ELD for integrated power system in presence of stochastic wind generation. In [39], the authors have used distributed gradient algorithm for solving ELD in case of stochastic networks. In addition, the dynamic programming based on rejectable deep differential for integrated generation dispatch and control framework is presented in [40].

Recently, the Turbulent Flow of Water Optimization (TFWO) for solving global real-world optimization problems is proposed by Ghasemi *et al.* [41]. The inspiration source for TFWO is based on the behaviour of whirlpools created in turbulent flow of water. As mentioned in the original paper, TFWO has provided an evidence in solving various optimization problems such as real-world engineering problems and standard benchmark compared to other MHs. Moreover, the prime motivation behind this is the No Free Lunch (NFL) theorem [42], [43]. NFL theorem states that a single algorithm does not perform equally well on all the optimization problems. Hence, the TFWO performance is tested for different networks such as ELD with transmission losses and CEED with and without the effect of valve point.

The results of TFWO is compared with eight other algorithms such as Cuckoo Search Algorithm (CSA) [44], Grey Wolf Algorithm (GW) [45], Sine Cosine Algorithm (SCA) [46], Earth Worm Optimization Algorithm (EWA) [47], Tunicate Swarm Algorithm (TSA) [48], Moth Search Algorithm (MSA) [49] and Teaching Learning Based Optimization (TLBO) [50]. The results revealed the superiority of the TFWO comparing to the other counterparts.

In summary, the main contributions of this paper are:

- Analysis of three cases network such as economic load dispatch (ELD) with transmission losses and Combined Economic and Emission Dispatch (CEED) with and without the effect of valve point.
- Turbulent flow of water based optimization algorithm is applied as a new metaheuristic algorithm for the three network cases of ELD problems.
- The objective function for the ELD is minimizing the cost fuel function. Minimizing the cost of fuel and emission is applied to CEED with and without the effect of valve point.
- Comparison between TFWO algorithm and other algorithms such as Cuckoo search algorithm (CSA), Grey wolf algorithm (GW), Sine cosine algorithm (SCA), Teaching learning based optimization (TLBO), Earth worm optimization algorithm (EWA), Tunicate swarm algorithm (TSA), and Moth search algorithm (MSA) is performed.
- The evaluation of TFWO and all algorithms performance is performed according the power mismatch between the generated power and the load demand with transmission losses.
- Statistical analysis is performed for running 30 independent runs of all algorithms and the robustness and convergence curves are discussed.

The organization of paper is as follows. The ELD problem is elaborates in section II, then Section III presents Turbulent Flow of Water Optimization (TFWO) overview. Section IV discusses the experimental results analysis. Finally, Section V discusses the conclusion and draw directions of the future work.

II. ECONOMIC LOAD DISPATCH PROBLEM

The operation and planning of power system has several problems such as ELD problem. The main contribution of ELD problem is maximizing the power system economic benefit and minimizing the net cost of fuel consumption based on allocating the optimal production of each unit. The following subsections discuss the three cases applied in this work such as ELD with losses, CEED with and without valve point effect.

A. ECONOMIC LOAD DISPATCH (ELD) WITH LOSSES

The ELD with losses can be expressed with the following analysis. The fuel consumption cost of n generators is explained as the following equation:

$$\mathrm{Min}(F) = F_1(P_1) + \cdots F_n(P_n) \tag{1}$$

where F is the net fuel cost, F_1 is the 1st generator fuel cost and F_n is the nth generator fuel cost.

The function of fuel cost is further approached in quadratic equation as:

$$\mathrm{Min}(F) = \sum_{k=1}^{n} F_i(P_i) = \sum_{k=1}^{n} a_k P_k^2 + b_k P_k + c_k \tag{2}$$

where a, b, c are the fuel cost weight constants. The constraints of each generator unit for minimizing the fuel cost is explained by equation (3) and (5).

$$\sum_{k=1}^{n} P_k - P_D - P_L = 0 \tag{3}$$

where the network net demand is represented by P_D and P_L is the transmission network losses.

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j \tag{4}$$

where B_{ij} is the coefficient of losses, P_i is the ith generator generated power, and P_j is the jth generator generated power.

$$P_k^{min} \le P_k \le P_k^{max} \tag{5}$$

B. COMBINED ECONOMIC LOAD DISPATCH (CEED)

The ELD problem is developed with taking into consideration the production cost and the reduction of emission, hence this problem is called Combined Emission and Economic Dispatch (CEED). The main contribution of CEED problem is minimizing the net cost of fuel consumption and also reduction the emission; based on that allocating the optimal production of each unit is performed.

The minimizing of gases emission from power plants is the main issue on emission dispatch problem. The emission factor is explained mathematically by:

$$Min(E) = \sum_{k=1}^{n} E_i(P_i) = \sum_{k=1}^{n} \alpha_k P_k^2 + \beta_k P_k + \gamma_k \tag{6}$$

The CEED objective function is:

$$objectivefunction = Min\left(\sum_{k=1}^{n} E_i(P_i) + h_e \sum_{k=1}^{n} F_i(P_i)\right) \tag{7}$$

where h_e is the price penalty factor as in equation 8:

$$h_e = \frac{F_i(P_{imax})}{E_i(P_{imax})} \tag{8}$$

The constraints of variable is given by equations (3) and (5).

C. CEED WITH VALVE POINT EFFECT

The effect of valve point is appeared in steam turbines due to it have multiple valves. The function of cost is nonlinear due to effect of valve point as in equation 9:

$$Min(F) = \sum_{k=1}^{n} F_i = \sum_{k=1}^{n} a_k P_k^2 + b_k P_k + c_k + |e_k \sin(f_k \times (P_{kmin} - P_k))| \tag{9}$$

where e_k and f_k are the valve point effect coefficients of kth generator. The main concern of optimization problem is minimized the emission and fuel cost of network based on the objective function of each network and the constraints illustrated in equations (3) and (5).

III. TURBULENT FLOW OF WATER-BASED OPTIMIZATION

Turbulent Flow of Water-based Optimization (TFWO) [41], is a modern powerful optimization algorithm for solving a complex problem inspired by the random activity of nature found in rivers, seas, and oceans, i.e. whirlpools formed in a turbulent flow of water For global real-world optimization problems. In whirlpools, the whirlpool's center acts as a sucking hole, drawing objects and particles around it towards the whirlpool's center and interior. The TFWO algorithm divides the population into NWh groups and places the best member of each group in the whirlpool's center.

A. WHIRLPOOLS: THEIR ORIGINS AND EFFECTS

The algorithm's initial population ((x^0), which contains N_p members) is evenly divided into N_{Wh} groups or whirlpool sets. Then the most vital member of each whirlpool set (the member with the highest objective function values f ()) is considered the whirlpool that pulls the objects (X, which contains N_p - N_{Wh} objects).

Each whirlpool(Wh), pulls objects toward their center by applying a centripetal force and unites their respective objects, then it suctions their objects and pours them into the sound. As a result, the *jth* whirlpool, with its local position on Wh_j, acts so that it unifies the position of the ith object (X_i) with that of itself, i.e., $X_i = Wh_j$. Other whirlpools, however, cause some deviations (X_i), depending on the distance between them (Wh-Wh_j) and the objective values (f (). As a result, the new position of the ith object is equal to $X_i^{new} = Wh_j - \Delta X_i$

The items (X) move with a peculiar pattern around the central point (δ) and near it. Thus, this position in the algorithm is constantly rotating:

$$\delta_i^{\text{new}} = \delta_i + \text{rand}_1 \times \text{rand}_2 \times \pi \tag{10}$$

To measure ΔX_i, Eq. 11 is used to calculate the farthest and nearest whirlpools (Δ_t), i.e. the whirlpools with the most and least weighted distance from all items, and then Eq. 12 is used to calculate (Δ_{X_i}). The particle's location is modified (X_i^{new}) using Eq.13.

$$\Delta_t = f\,(Wh_t) \times |Wh_t - \text{sum}\,(X_i)|^{0.5} \tag{11}$$

$$\begin{aligned}\Delta X_i = {} & (\cos(\delta_i^{\text{new}}) \times \text{rand (1,D)} \times (Wh_f - X_i) \\ & - \sin\left(\delta_i^{\text{new}}\right) \times \text{rand}(1, D) \times (Wh_w - X_i)\big) \\ & \times \left(1 + \left|\cos\left(\delta_i^{\text{new}}\right) - \sin\left(\delta_i^{\text{new}}\right)\right|\right)\end{aligned} \tag{12}$$

$$X_i^{\text{new}} = Wh_j - \Delta X_i \tag{13}$$

where Wh_f and Wh_W are the whirlpools with the lowest and highest Δ_t, respectively, and δ_i is the angle of the *ith* object.

B. THE MATHEMATICAL MODEL

This part summarizes the mathematical steps necessary to implement the TFWO algorithm:

1) *The phase of updating an object's position:* The following two steps summarize the phase of updating an object's position:
Step 1:
for t = 1 N_{Wh}
$\Delta_t = f(Wh_t) \times |Wh_t - sum(X_i)|^{0.5}$
end
$Wh_f = Wh_t$ with min value of Δ_t
$Wh_w = Wh_t$ with max value of Δ_t
$\delta_i^{\text{new}} = \delta_i + \text{rand}_1 \times \text{rand}_2 \times \pi$
$\Delta X_i =$
$\left(\cos\left(\delta_i^{\text{new}}\right) \times \text{rand}\,(1, D) \times \left(Wh_f - X_i\right)\right.$
$\left. - \sin\left(\delta_i^{\text{new}}\right) \times \text{rand}(1, D) \times (Wh_w - X_i)\right)$
$\times \left(1 + \left|\cos\left(\delta_i^{\text{new}}\right) \times - \sin\left(\delta_i^{\text{new}}\right)\right|\right);$
$X_i^{\text{new}} = Wh_j - \Delta X_i;$
Step 2:
$X_i^{\text{new}} = \min\left(\max\left(X_i^{\text{new}}, X^{\min}\right), X^{\max}\right);$
if $f\left(X_i^{\text{new}}\right) <= f\,(X_i)$
$X_i = X_i^{\text{new}}$
$f\,(X_i) = f\left(X_i^{\text{new}}\right);$
end

2) *Centrifugal force phase:* According to Newton's first law of motion, Unless acted upon by an unbalanced force, an object at rest will remain at rest, and an object in motion will remain in motion with the same speed and direction. The centrifugal force (FE_i) may often overpower the whirlpool's centripetal or traction force, causing the object to move randomly. We've used Eq. 14 to model the centrifugal force, which arises at random in one of the decision variables' dimensions. To do so, first, calculate the centrifugal force based on the angle between the target and the whirlpool (as Eq. 15), then see if it is greater than a random amount.Step 3 summarizes the mathematical model for the centrifugal force phase.

$$FE_i = \left(\left(\cos\left(\delta_i^{\text{new}}\right)\right)^2 \times \left(\sin\left(\delta_i^{\text{new}}\right)\right)^2\right)^2 \tag{14}$$

$$x_{i,p} = x_p^{\min} + rand \times \left(x_p^{\max} - x_p^{\min}\right) \tag{15}$$

Step 3:
$FE_i = \left(\left(\cos\left(\delta_i^{\text{new}}\right)\right)^2 \times \left(\sin\left(\delta_i^{\text{new}}\right)\right)^2\right)^2.$
if rand $< FE_i$
$p = \text{round}(1 + \text{rand} \times (D - 1));$
$x_{i,p} = x_p^{\min} + \text{rand} \times \left(x_p^{\max} - x_p^{\min}\right);$
$f\,(X_i) = f\left(X_i^{\text{new}}\right);$
end

3) *Whirlpool interactions:* Like how a whirlpool interacts with and displaces its surroundings, they also interact with and displace one another. This effect has been modeled similarly to how whirlpools affect objects. Each whirlpool has a natural tendency to attract other whirlpools, exert centripetal force on them, and

TABLE 1. Different cases of ELD considered in analysis.

Case	Description	Test system	Demand (MW)
1	ELD	6	700 1000 1200
2	CEED	6	700 1000 1200
3	CEED with valve point effect	10	2000

submerge them in their wells (i.e., unify the considered whirlpool position with its position). The nearest whirlpool is determined first, using its objective function and the smallest amount of Eq (16) to simulate this effect. Then, Eqs. (17) and (18) are used to determine the position of the whirlpool.

$$\Delta_t = f(Wh_t) \times \left|Wh_t - sum(Wh_j)\right| \quad (16)$$

$$\Delta Wh_j = rand(1, D) \times \left|cos(\delta_j^{new}) + sin(\delta_j^{new})\right| \times (Wh_f^{new} - Wh_j^{new}) \quad (17)$$

$$Wh_j^{new} = Wh_f - \Delta Wh_j \quad (18)$$

where δ. denotes the angle of the j^{th} whirlpool hole. Steps 4 and 5 demonstrate the relationship between whirlpool interactions and are used to summarize the above phenomenon:

Step 4:
for t = 1: $N_{Wh} - j$
$\Delta_t = f(Wh_t) \times \left|Wh_t - sum(Wh_j)\right|$ end
$Wh_f =$ Wh with min value of Δ_t
$Wh_j^{new} = Wh_f - \Delta Wh_j$;
$\Delta Wh_j = rand(1, D) \times \left|cos(\delta_j^{new}) + sin(\delta_j^{new})\right| \times (Wh_f^{new} - Wh_j^{new})$;
$\delta_j^{new} = \delta_j + rand_1 \times rand_2 \times \pi$.
Step 5:
$Wh_j^{new} = \min(\max(Wh_j^{new}, X^{min}), X^{max})$;
if $f(Wh_j^{new}) \leq f(Wh_j)$
$Wh_j = Wh_j^{new}$;
$f(Wh_j) = f(Wh_j^{new})$;
end

4) *The phase of selecting the best member:* If the best new member of the whirlpool's set outperforms its corresponding whirlpool, it is selected as the new whirlpool for the next iteration. Step 6 depicts the latest best whirlpool that has been chosen.
Step 6:
if $f(X_{best}) \leq f(Wh_j)$
$Wh_j \leftrightarrow X_{best}$
end

IV. EXPERIMENTAL RESULTS ANALYSIS AND DISCUSSION

The performance of TFWO on different scenarios of ELD is compared with other algorithms such as; Cuckoo Search Algorithm (CSA) [44], Grey Wolf Algorithm (GW) [45], Sine Cosine Algorithm (SCA) [46], Earth Worm Optimization Algorithm (EWA) [47], Tunicate Swarm Algorithm (TSA) [48], Moth Search Algorithm (MSA) [49] and Teaching Learning Based Optimization (TLBO) [50]. The performance of TFWO is analyzed for different cases of ELD as shown in Table 1.

This section reported the proposed TFWO results for solving ELD problem. Comparison between the competitor techniques and TFWO algorithm is discussed.

TABLE 2. Parameter settings of all algorithms.

Algorithms	Parameters setting
Common Settings	Population size: $N = 30$ Maximum iterations: $t_{max} = 1000$ Number of independent runs 30
TFWO	
SCA	$A = 2$
TLBO	$TF = \{1, 2\}$
GWO	a decreases linearly from 2 to 0
CSA	
TSA	P_{min}=1 and P_{max}=4 (Default)
EWA	α= 0.98, β_0 = 0.1, γ = 0.9
MSA	β_0 = 1.5, S_{max} = 1

TABLE 3. Statistical results of the experimental series 1: ELD problem.

Demand (MW)	Algorithm	min	mean	max	SD
700	TFWO	8453.76192	1379081.99	13082056.1	3296646.43
	SCA	907782.138	68065356.8	285344403	60444388.9
	TLBO	9019.36061	10925318.3	62924616.3	16170600.6
	GWO	362947.614	6046091.28	20685340.1	5465239.14
	CSA	18559.7269	827178.657	4343492.65	978763.025
	TSA	275801.527	13242490.7	43445577.3	11464055.7
	EWA	14082.2401	43232927.3	390748779	83438502
	MSA	8416.08767	8746.97462	9225.14196	180.245442
1000	TFWO	12164.5853	314535.872	3578493.72	756727
	SCA	740103.535	88782958.5	222530268	67692758.5
	TLBO	13926.3065	13749662.6	72600497.8	17910396.5
	GWO	285622.639	9101405.82	26944657.8	6706299.6
	CSA	28313.2238	505104.661	2689533.25	626323.447
	TSA	77930.9845	16058610.3	45829971	14684516.5
	EWA	49087.2012	21265097.6	115431147	28637807.3
	MSA	12129.8801	12282.1503	12592.0808	100.389703
1200	TFWO	14867.2231	528582.834	3954992.4	954834.858
	SCA	1268040.81	207184312	465738288	129555600
	TLBO	24455.3253	4346071.08	21567599	5189973.72
	GWO	798811.425	10825902.3	28975810.3	9103573.43
	CSA	31815.2192	2259672.72	9632243.88	2732490.15
	TSA	1020643.54	21140672.4	84567435.2	20443391.4
	EWA	17595.5608	161035562	882270106	225076551
	MSA	14856.588	14927.2252	15044.0576	46.3826663

TABLE 4. Best costs for different demand value of case 1 in $ per hour.

Algorithm	700 MW	1000 MW	1200 MW
TFWO	8453.76192	12164.5683	14867.2231
SCA	8977.36522	12229.5632	14921.6636
TLBO	8957.12833	12181.0506	15038.6454
GWO	8871.22926	12797.6456	14939.5775
CSA	8691.6761	12186.2742	14919.5663
TSA	8755.28822	12368.0809	14930.4879
EWA	9073.6947	13820.0655	18038.3241
MSA	9921.94843	14263.3788	17163.8795

A. PARAMETER SETTINGS

For fair comparison, the parameters setting of each algorithm is reported in table 2.

B. EXPERIMENTAL SERIES 1: THE ELD PROBLEM

The ELD problem is solved for 6-unit system for the load demands shown in Table 1 by the algorithms mentioned in Table 2. Table 3 presents the statistical comparison of the

TABLE 5. Allocation vector for 700 MW of case 1 at best objective function.

TFWO	SCA	TLBO	GWO	CSA	TSA	EWA	MSA
279.70647	100	103.079581	103.191452	163.882794	141.305386	54	50.0166154
53.7350452	57.291274	50.0000286	161.913376	118.483692	200	62.7600473	50.0740601
124.780909	186.671592	224.21128	161.291166	146.726141	171.907561	96.6647418	82.4313911
98.2733336	150	89.3033024	101.718418	50	51.7078763	120.556948	95.5309411
102.455809	171.171305	199.002992	135.551449	138.749038	98.1461498	145.578577	104.549086
52.8326254	50	50	50	95.4691493	50	203.292193	328.40613

TABLE 6. Allocation vector for 1000 MW of case 1 at best objective function.

TFWO	SCA	TLBO	GWO	CSA	TSA	EWA	MSA
411.094183	313.955109	340.087152	135.888893	380.765127	290.414644	88.1573367	50.0232365
96.2654945	196.890827	116.160462	199.001016	124.989153	183.333019	91.8663096	57.237545
185.468484	200.61033	242.047927	294.665653	187.668323	296.338687	105.787269	132.647259
124.121701	112.611771	92.6391316	128.396045	119.44231	150	113.663678	145.799425
138.10152	150.830348	149.168555	172.302205	101.019063	50	295.689453	221.52656
68.7556101	5.00E+01	85.1210498	98.6973324	110.017034	55.2138696	330.135192	416.147459

TABLE 7. Allocation vector for 1200 MW of case 1 at best objective function.

TFWO	SCA	TLBO	GWO	CSA	TSA	EWA	MSA
423.663636	462.791999	500	498.864855	499.605748	477.306095	86.1251182	77.7295385
147.788068	167.236572	50	96.0242331	190.931523	192.905792	106.482075	137.508053
273.623451	300	300	220.873051	185.547242	295.675102	171.917379	138.992873
141.281259	50	150	144.599474	143.940165	145.727481	176.159478	145.170595
187.078697	200	186.287678	199.996288	117.125234	68.830457	261.237939	256.069967
62.7158386	55.750911	50	75.0171419	96.1454203	53.011574	495	478.937148

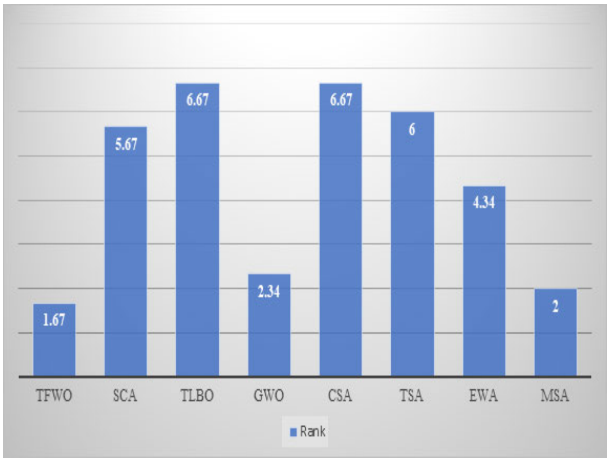

FIGURE 1. Test of Friedman rank for algorithms at case 1.

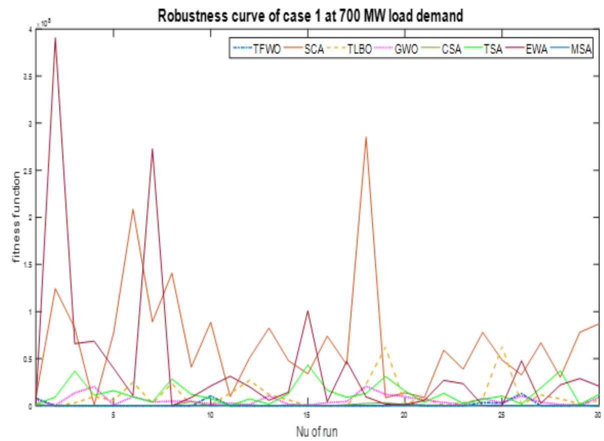

FIGURE 2. Robustness curves of 700 MW for case 1.

performance of TFWO with other algorithms. It is observed that TFWO is equally competitive as compared to other MHs. Table 4 presents the best costs for different demand value of case 1 in $ per hour. It is observed that TFWO yields the best cost for all the load demands mentioned in Table 2. Tables 6, 7 and 8 presents the allocation vector for load demand 700, 1000, and 1200 MW respectively. Based on this results, the best fuel cost function is 14867.2231, 12164.5683 and 8453.76192 that is achieved by TFWO algorithm for 1200 MW, 1000 MW and 700 MW load demand respectively. The order of algorithms according to the best objective function for 700 MW demand are as follow; TFWO, CSA, TSA, GWO, TLBO, SCA, EWA and MSA respectively. The order of algorithms according to the best objective

TABLE 8. Statistical results of case 2.

Demand (MW)	Algorithm	min	mean	max	SD
700	TFWO	13712.6821	326761.658	4791878.67	890375.044
	SCA	3498899.46	81866344.3	214596827	63677233.2
	TLBO	14123.048	8755556.15	34473506.6	9072878.41
	GWO	29018.611	5429748.37	25373851.5	5749710.12
	CSA	65325.6086	1293088.8	6254924.43	1593036.44
	TSA	281742.814	13248261.7	43451402.6	11464095
	EWA	15160.1414	44386744	341883986	74160339.4
	MSA	13575.7511	14585.8734	16052.6875	696.601179
1000	TFWO	21632.8911	338731.208	6098354.78	1196846.8
	SCA	1066951.63	77047657.2	234869078	62697039.5
	TLBO	22904.684	7256982.8	22234281.1	7023905.71
	GWO	162179.528	9182747.2	47744950.8	10275947
	CSA	24724.3426	798194.46	4308128.09	1098550.55
	TSA	83113.3798	21500100.8	78831952.8	18405207.9
	EWA	31143.6099	28014658.8	205671456	45866455.5
	MSA	21622.8477	22187.6535	23747.1207	434.056923
1200	TFWO	27978.3384	541957.3	3968159.64	954748.052
	SCA	1281581.91	207198002	465751980	129555644
	TLBO	38605.7719	4359495.81	21581025.7	5189942.6
	GWO	812279.135	10839323.8	28989242.2	9103601.12
	CSA	45247.9944	2273109.79	9645398.76	2732478.13
	TSA	109863.585	17394994.5	68229764.1	14835975.2
	EWA	43957.236	97054433.5	548931523	140908416
	MSA	28022.6494	28367.5779	28693.4463	178.832667

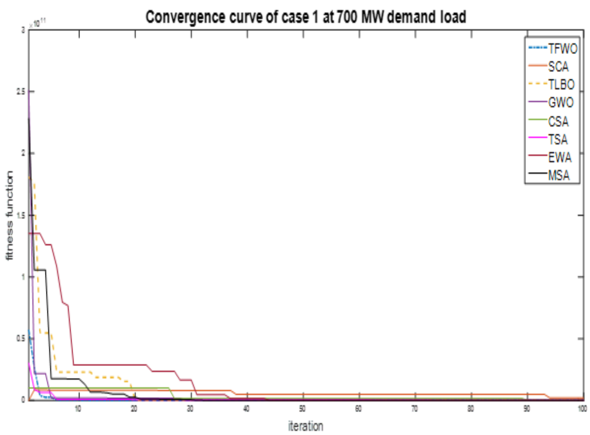

FIGURE 3. Convergence curves of 700 MW for case 1.

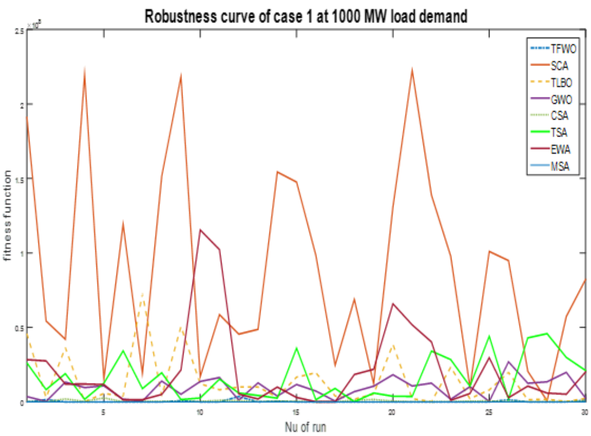

FIGURE 4. Robustness curves of 1000 MW for case 1.

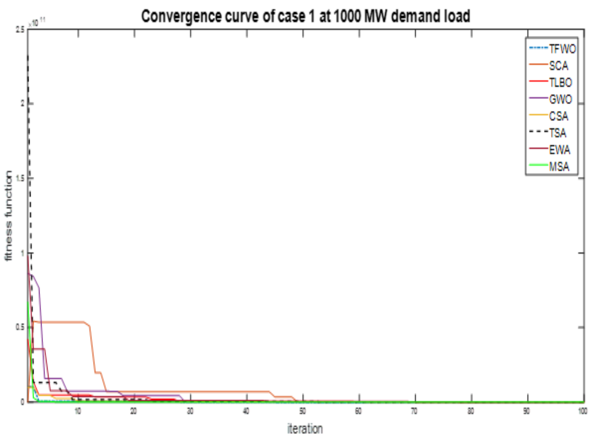

FIGURE 5. Convergence curves of 1000 MW for case 1.

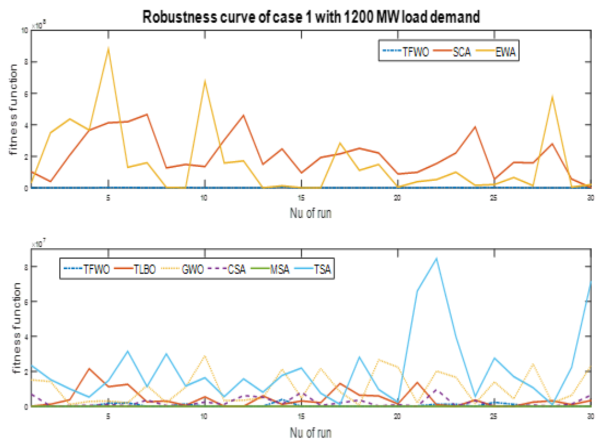

FIGURE 6. Robustness curves of 1200 MW for case 1.

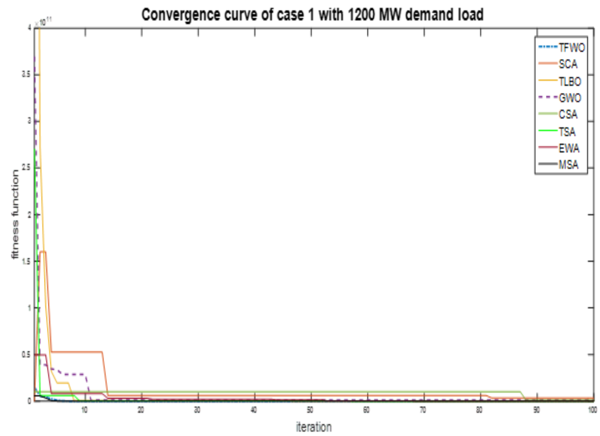

FIGURE 7. Convergence curves of 1200 MW for case 1.

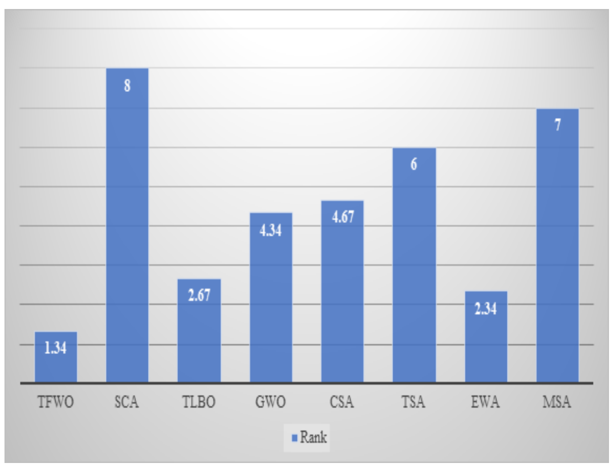

FIGURE 8. Test of Friedman rank for algorithms at case 2.

function for 1000 MW demand are as follow; TFWO, TLBO, CSA, SCA, TSA, GWO, EWA and MSA respectively. The order of algorithms according to the best objective function for 1200 MW demand are as follow; TFWO, CSA, SCA, TSA, GWO, TLBO, MSA and EWA respectively.

Fig. 1 explains the Friedman ranks of all algorithms for case 1. Based on this figure ; the best rank is achieved by TFWO then MSA, GWO, EWA, SCA, TSA, TLBO and CSA respectively. Fig. 2, Fig. 4, and Fig. 6 presents the robustness curve of the algorithms for load demands 700, 1000, and 1200 MW respectively. Fig. 3, Fig. 5, and Fig. 7 presents

TABLE 9. Best costs for different demand value of case 2 in $ per hour.

	700 MW		1000 MW		1200 MW	
Algorithm	fuel	emission	Fuel	emission	fuel	emission
TFWO	8484.7492	5334.43591	12153.53672	10350.3571	14868.83888	14011.91431
SCA	8753.8071	11824.5127	12450.06933	9108.129083	14921.66359	16011.32313
TLBO	8645.3535	6370.89591	12426.65607	7580.593553	15038.64541	18149.24197
GWO	8855.721	6069.06129	12193.42527	10861.57216	14939.57752	14493.96991
CSA	8510.7373	6296.13667	12179.40721	12622.4496	14919.56628	13559.82202
TSA	8755.2882	5719.80766	12514.19328	13089.89644	14879.37634	16403.29639
EWA	9354.1225	10875.91	12751.47862	26975.8048	15194.94776	32022.12828
MSA	9488.9578	14610.4574	14209.44378	37140.9	17131.55584	51189.43662

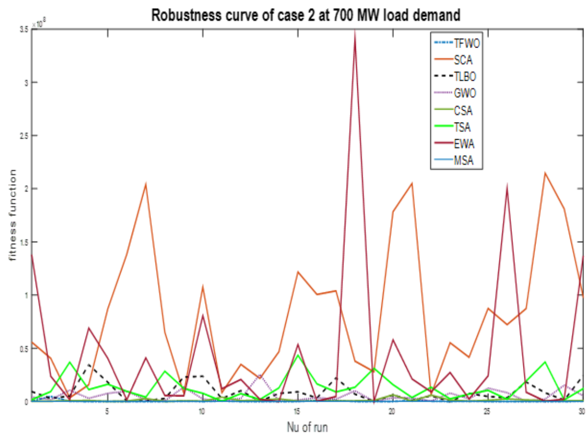

FIGURE 9. Robustness curves of 700 MW for case 2.

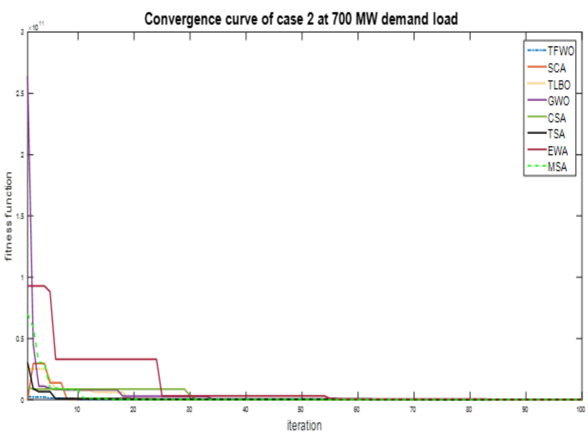

FIGURE 10. Convergence curves of 700 MW for case 2.

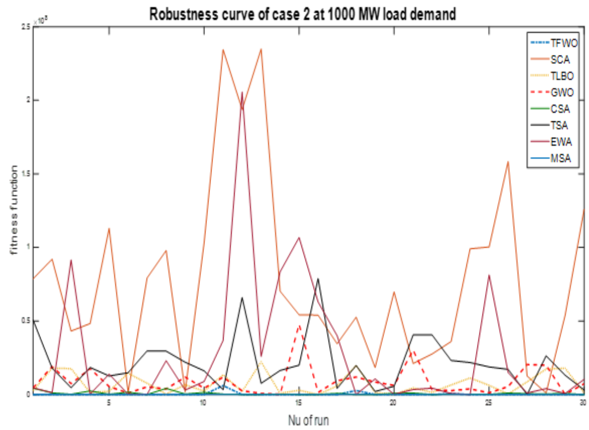

FIGURE 11. Robustness curves of 1000 MW for case 2.

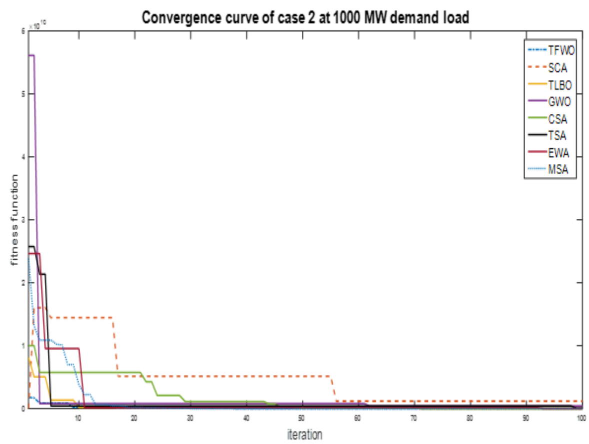

FIGURE 12. Convergence curves of 1000 MW for case 2.

the convergence curve for load demands 700, 1000, and 1200 MW respectively. It is observed that the probability of getting stuck in local optima is rare in case of TFWO and it favors faster convergence.

C. EXPERIMENTAL SERIES 2: THE CEED PROBLEM FOR 6 UNIT SYSTEM

The CEED problem is solved for 6 unit system for the load demands shown in Table 1 by the algorithms mentioned in Table 2. In case of CEED both cost and emission are given equal importance. Table 8 presents the statistical comparison of the performance of TFWO with other MHs. It is observed that TFWO is equally competitive as compared to other MHs. Table 9 presents the best costs for different demand value of case 2 in $ per hour. It is observed that TFWO yields the best cost for all the load demands mentioned in Table 2. Tables 10, 11, and 12 presents the allocation vector for load demand 700, 1000, and 1200 MW respectively. Based on this results, the best fuel cost function is 14868.8388, 12153.5367 and 8484.7923 that is achieved by TFWO algorithm for 1200, 1000 and 700 MW load demand respectively. The order of algorithms according to the best objective function for 700 MW demand are as follow; TFWO, CSA, TLBO, SCA, TSA, GWO, EWA and MSA respectively.

TABLE 10. Allocation vector for 700 MW of case 2 at best objective function.

TFWO	SCA	TLBO	GWO	CSA	TSA	EWA	MSA
249.229677	162.34628	159.910043	134.532478	290.589017	141.305386	59.0339797	75.3858552
138.708474	80.050332	102.238522	139.034345	57.0713497	200	64.0807746	78.0775515
127.543045	300	185.305227	110.739476	109.869376	171.907561	120.98096	79.5353854
82.5535986	55.973674	62.3310903	141.556111	89.1526351	51.7078763	132.216799	92.8517453
50.0005931	50	148.916354	114.011476	65.5363436	98.1461498	155.962314	133.308168
63.3666854	65.840722	54.7532276	73.5439384	99.3796702	50	182.017735	252.548458

TABLE 11. Allocation vector for 1000 MW of case 2 at best objective function.

TFWO	SCA	TLBO	GWO	CSA	TSA	EWA	MSA
348.695845	500	500	484.388312	470.298949	219.413652	53.631972	76.1226548
166.683635	50	143.240374	73.5859262	106.523319	200	71	81.6338614
213.740597	102.906171	80	201.995003	254.23611	266.536515	103.99366	96.8360107
109.147997	92.049489	50	92.7853309	67.5116817	50	111.010881	115.19833
131.911042	200	200	119.73716	70.3426938	176.749382	238.97893	231.648118
54.0637884	79.2047469	50.0378964	50	53.3426186	114.918881	349.988739	422.05644

TABLE 12. Allocation vector for 1200 MW of case 2 at best objective function.

TFWO	SCA	TLBO	GWO	CSA	TSA	EWA	MSA
496.100544	462.791999	500	498.864855	499.605748	500	81.4513192	95.9965098
180.463022	167.236572	50	96.0242331	190.931523	126.516088	100.000045	99.9406786
228.606689	300	300	220.873051	185.547242	282.926534	194.998712	138.83767
84.7009078	50	150	144.599474	143.940165	126.620457	199.99994	199.999793
147.526063	200	186.287678	199.996288	117.125234	146.970176	221.999973	215.998151
96.3920018	55.7509113	50	75.0171419	96.1454203	51.1752392	343	483.015011

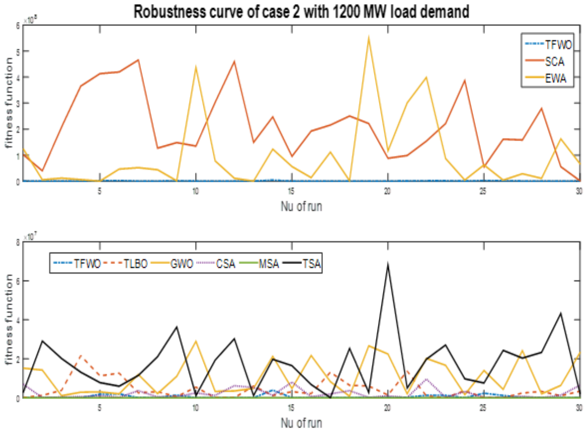

FIGURE 13. Robustness curves of 1200 MW for case 2.

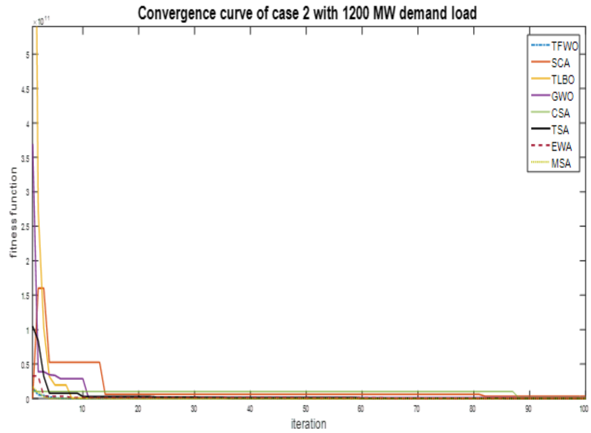

FIGURE 14. Convergence curves of 1200 MW for case 2.

TABLE 13. Statistical results of case 3.

Demand (MW)	Algorithm	min	mean	max	SD
	TFWO	220423.06	598281.65	4958733.292	944175.481
	SCA	15101022	1649046188	11581460323	2278649761
	TLBO	222513.64	5161540.32	27406924.45	5560297.39
	GWO	1120984.99	19560051.6	89572855.13	17846261.7
	CSA	3645229.16	6226255148	10000000000	4729960096
	TSA	3528495.67	38134328.4	105778137.5	29707313.3
2000	EWA	542621.782	2897510479	29289503125	5800651131
	MSA	221324.598	30649281.2	912903764.8	166631270

TABLE 14. Costs at the best objective function for case 3.

Demand (MW)	Algorithm	Fuel cost with valve ($ per hour)	Fuel cost without valve ($ per hour)	Emission (lb)
	TFWO	112148.878	1.33E+05	4516.249847
	SCA	117427.0522	132623.5573	4431.130249
	TLBO	115164.581	132623.5573	4159.008489
	GWO	114881.3939	132623.5573	4301.335899
	CSA	112930.8597	132623.5573	4316.810294
	TSA	115538.0166	132623.5573	4433.283284
2000	EWA	100846.3372	132623.5573	3605.571137
	MSA	114284.2979	132623.5573	4061.89121

The order of algorithms according to the best objective function for 1000 MW demand are as follow; TFWO, CSA, GWO, TLBO, SCA, TSA, EWA and MSA respectively. The order of algorithms according to the best objective function for 1200 MW demand are as follow; TFWO, TSA, CSA, SCA, GWO, TLBO, EWA and MSA respectively.

Fig. 8 explains the Friedman ranks of all algorithms for case 2. It is observed that TFWO has achieved the best rank followed by EWA, TLBO, GWO, CSA, TSA and SCA respectively. Fig. 9, Fig. 11, and Fig. 13 presents the robustness curve of the algorithms for load demands 700, 1000, and 1200 MW respectively. Fig. 10, Fig. 12, and Fig. 14 presents the convergence curve for load demands 700, 1000, and 1200 MW respectively.

D. EXPERIMENTAL SERIES 3: THE CEED PROBLEM FOR 10 UNIT SYSTEM

The CEED problem considering valve point effect is solved for 10 unit system for the load demands shown in Table 1

TABLE 15. Allocation vector for 2000 MW of case 3 at best objective function.

TFWO	SCA	TLBO	GWO	CSA	TSA	EWA	MSA
35.8593741	10	54.2923587	18.1864836	54.8791241	10.5605925	21.8488406	49.799428
73.541012	20	77.9370289	43.7414724	51.9410131	23.5795537	51.0615497	79.9991336
119.432799	47	98.2565919	92.8617652	119.589725	73.4974903	71.4357504	86.6114236
128.607768	29	112.099482	34.3502021	67.2280635	90.4144438	106	96.0298499
89.5279508	160	95.1258708	133.31944	158.961773	72.5558797	119.609712	130.775676
109.263695	240	235.01898	203.021473	73.211088	240	153.89698	192.924051
256.05867	300	187.238452	296.190367	299.977904	294.996104	197.81122	299.9983
333.452184	340	323.546554	339.241033	340	340	238.025893	336.560815
470	470	467.179159	459.374178	457.613463	470	449.460184	339.847821
470	470	432.969966	465.407542	463.030817	470	456.59392	469.850154

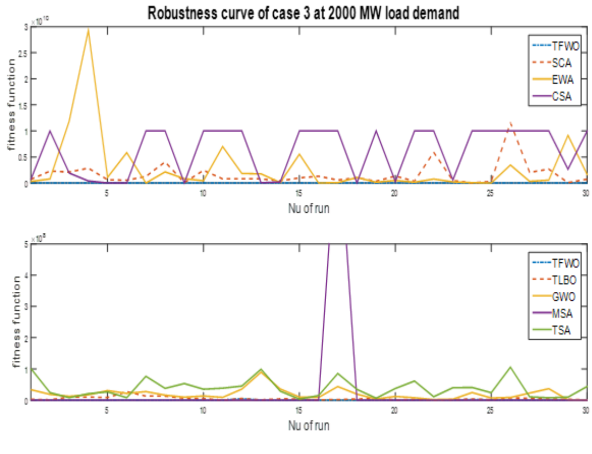

FIGURE 15. Robustness curves of 2000 MW for case 3.

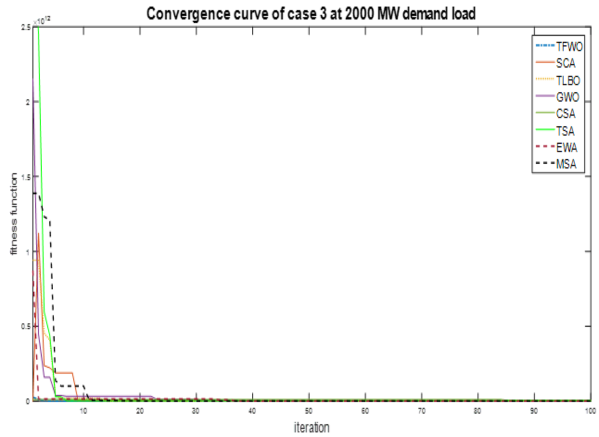

FIGURE 16. Convergence curves of 2000 MW for case 3.

by the algorithms mentioned in Table 2. Table 13 presents the statistical comparison of the performance of TFWO with other MHs. It is observed that TFWO is equally competitive as compared to other MHs. Table 14 presents the best costs of case 3 in $ per hour. It is observed that TFWO yields the best cost for all the load demands mentioned in Table 2. Table 15 presents the allocation vector for load demand 2000 MW respectively.

Fig. 15 presents the robustness curve of the algorithms for load demand 2000 MW. Fig. 16 presents the convergence curve. It is observed that the probability of getting stuck in local optima is rare in case of TFWO and it favors faster convergence.

E. DISCUSSION

The absolute difference between the sum of generated power from each unit in the network and the sum of load demand and transmission losses is called power mismatch. This should be ideally zero and it is considered as a soft constraint in the optimization problem. Based on the results extracted for the three tested network; ELD, CEED with and without effect of valve point, the term power mismatch is determined from these results. Table 16 explain the value of power mismatch for all cases. The more accurate result extracted from any algorithm is the result that achieve the smallest value of power mismatch. Based on the results recorded in Table 16; the proposed TFWO algorithm achieve the best value of power mismatch for all demands in all cases is reported in Table 16. Hence; the TFWO algorithm is more accurate and reliable so that the proposed TFWO is superior on all competitor algorithms used in the ELD problem.

TABLE 16. The value of power mismatch for all cases.

Cases	Algorithm	700 MW	1000 MW	1200 MW	2000 MW
	TFWO	**2.20E-13**	**1.71E-12**	**6.54E-13**	-
	SCA	8.99E-05	7.28E-05	1.25E-04	-
	TLBO	6.22E-09	1.75E-07	9.42E-07	-
	GWO	3.54E-05	2.73E-05	7.84E-05	-
	CSA	9.87E-07	1.61E-06	1.69E-06	-
	TSA	2.67E-05	6.56E-06	0.00010057	-
Case 1	EWA	32.6253734	1.18E+01	36.2637036	-
	MSA	8.72410542	1.65E+01	20.6804214	-
	TFWO	**7.67E-13**	**2.13E-13**	**1.99E-13**	-
	SCA	3.48E-04	1.04E-04	1.25E-04	-
	TLBO	2.01E-10	2.00E-10	9.42E-07	-
	GWO	1.40E-06	1.40E-05	7.84E-05	-
	CSA	5.14E-06	2.71E-07	1.69E-06	-
	TSA	2.67E-05	5.99E-06	8.16E-06	-
Case 2	EWA	2.06340623	103.487379	101.595081	-
	MSA	5.50286239	16.2276651	21.2674607	-
	TFWO	-	-	-	**8.24E-13**
	SCA	-	-	-	1.49E-03
	TLBO	-	-	-	6.86E-08
	GWO	-	-	-	8.90E-05
	CSA	-	-	-	0.00034215
	TSA	-	-	-	0.00032945
Case 3	EWA	-	-	-	203.313641
	MSA	-	-	-	0.61243059

V. CONCLUSION AND FUTURE WORK

Economic Load Dispatch (ELD) is one of the complex problems of power system. In this study, an efficient new algorithm termed Turbulent Flow of Water-based

Optimization (TFWO) is proposed to solve different variants of ELD such as ELD with losses, Combined Economic and Emission Dispatch (CEED), and CEED considering valve point effect. TFWO is a recent MH inspired from whirlpools created in turbulent water flow. TFWO has good balance between exploration and exploitation. Also, the possibility of getting stuck in local optima and premature convergence is rare in TFWO. Three experimental series such as; the ELD problem, the CEED problem for 6 unit system and the CEED problem for 10 unit system are utilized in this paper. The performance of TFWO is compared with seven algorithms such as Cuckoo Search Algorithm (CSA), Grey Wolf Algorithm (GW), Sine Cosine Algorithm (SCA), Earth Worm Optimization Algorithm (EWA), Tunicate Swarm Algorithm (TSA), Moth Search Algorithm (MSA) and Teaching Learning Based Optimization (TLBO) for different demands. Eventually, The numerical results show that the TFWO algorithm has superior merits, advantages over other counterparts in terms of robustness, avoids premature convergence, and stable convergence characteristic. The future work will concentrates on; 1) although, the TFWO is applied to solve ELD problems in the current study, it seems that TFWO has the potential to solve many other optimization problems in the field of power system planning and operation such as unit commitment, charger placement, and optimal power flow. 2) studding the ELD on resources of renewable energy using TFWO algorithm.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CREDIT AUTHOR STATEMENT

All authors contributed equally to this paper, where; Sanchari Deb: Formal analysis, Resources, Writing - review & editing. Essam H. Houssein: Supervision, Methodology, Conceptualization, Formal analysis, Writing - review & editing. Mokhtar Said: Software, Formal analysis, Resources, Writing - original draft. Diaa Salama AbdElminaam: Resources, Data Curation, Writing - review & editing. All authors read and approved the final paper.

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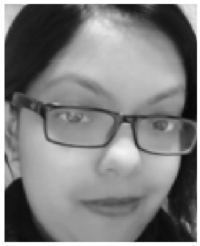

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