Multi-Period Economic Load Dispatch with Wind Power Using a Novel Metaheuristic

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ABSTRACT

This paper provides a conventional cooperation strategy of thermal power plants (TPPs) in economic load dispatch (ELD) problem and proposes a new cooperation strategy of TPPs and wind farms (WFs) in modified ELD (MELD) problem. The main target while solving both ELD and MELD problems is to cut total fuel cost (TFC). Besides, the generating capacity and prohibited zone operating constraints of each thermal power plant, the generation capacity of WFs, and the power balance of system are also considered. Moreover, the power balance constraint is modified by considering the power loss (*PLs*) and the power output of wind turbine (P_{wind}) in 24 periods. For finding the optimal operation parameters of ELD and MELD problems, Tunicate Swarm Optimizer (TSO) is nominated. TSO is a novel method with one generation of updating solutions per each iteration and it is simple for a typical optimization problem as well as complex problems. To value the real effectiveness of TSO, three systems with non-convex function and different constraints are employed. In which the first two systems are a standard system with TPPs while the last one formed from the second one considers the operation coordination of WFs and TPPs. Apart from TSO, social ski driver algorithm (SSD) and particle swarm optimization (PSO) are also implemented. The results by using TSO, PSO and SSD for the first two systems reveal that TSO is a strong method. The results on the last one prove the important role of wind power for the cost reduction. As a result, a conclusion is withdrawn that TSO is a good solution for solving ELD and MELD problems.

1. INTRODUCTION

The problem of economic load dispatch (ELD) is one of the chief optimization ones due to its significant distribution. This problem is to determine the power output of the existing units for the purpose of minimizing fuel cost and simultaneously meeting physical constraints. The fuel cost for operating the TPPs is high and becomes rare in future. This proves why the ELD problem is very important. In the first ELD problem, the function of TFC is normally represented under a single quadratic one and its constraints are very simple like power balance and the generating capacity limit. This type is successfully handled by some methods like Hopfield method (HM) [1], one rank cuckoo search (ORCS) [2], stochastic fractal search (SFS) [3], modified firefly optimizer (MFO) [4], elitist particle swarm optimization (EPSO) [5], biogeography-based learning particle swarm optimization (BLPSO) [6], improved firefly optimizer (IFO) [7] and clustering cuckoo search (CCS) [8]. However, the practical ELD problem is a complex one with high dimensional, non-convex function and non-smooth function. The non-convex function is because of existing the valve-point effects as shown in backtracking search (BS) [9], hybrid scheme Nelder–Mead and pattern search methods (NM–PS) [10] and variants of genetic algorithm (GAs) [11], GA with sequential quadratic programming (GA-SQP) [11] and GA with interior-point methods (GA-IPMs) [11]. The non-smooth function owns to using multiple fuel sources as presented in improved SFS (ISFS) [12] and improved spider optimizer (ISO) [13]. Apart from the mentioned functions, the operation constraint of unit to be prohibited operating zones in ELD also existed as reported in differential evolution (DE) [14], new adaptive particle swarm optimization (NAPSO) [15], exchange market search (EMS) [16], modified krill herd search (MKHS) [17], adaptive charged system search (ACSS) [18], modified moth swarm search (MMSS) [19] and improved cuckoo search (ICS) [20]. After reviewing

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all above papers, it shows that authors only focused on solving the generation scheduling but not considering pollution emission (PE) from TPPs. Recently, environment pollution is the hottest issue that gets the concern of social. Therefore, such PE from TPPs is first treated in most of countries. To reduce amount of PE, we need to find a new plant satisfying both electricity generation and PE decrease. Renewable energy plant (REP) is considered as an excellent measurement. So, ELD problem should be renewed by replacing the operation scheduling for TPPs to that of for TPPs and REPs. For valuing such ELD problem considering REPs, many intelligent optimization methods are favored by scholars [21-26]. In [21-23], the wind cost model such as direct cost, overestimation cost and underestimation cost are proposed. These costs are regarded as the objective function and added into the objective function of traditional ELD problem. In addition, authors in [21-22] have also suggested different hybrid systems (HSs) with the consideration of wind farm (WF) to test an ability of the proposed method. In [21], brain storm optimizer (BSO) is used to test on two hybrid systems with six units and one WF, and 40 units and one WF. Bat optimizer (BO) is recommended in [22] and is implemented on two HSs. In which, the first HS is the same as the first system in [21] and the second one includes 15 thermal units and one WF of 300MW. Dragonfly search (DS) has been applied in [23] and [24]. However, in [23] mixed system with WFs and TPPs is considered while a combination of TPPs with WFs and solar farms is employed in [24]. Unlike [21-24], direct cost of WF model in [25] is ignored and modified anti-predatory PSO (MAPSO) is suggested for valuing the effectiveness of WF as added into existing system. A study of dynamic power dispatch regarding the uncertainties of wind power penetration, effects of valve, limitation of ramp rate and violated working zones are recommended in [26]. Clearly, the ELD problem with the existence of REPs is more complex than original ELD problem. Therefore, handling this problem needs a strong enough tool for reaching a global solution in shorter implementation time and less generation assessments. Tunicate swarm optimizer (TSO) was a metaheuristic algorithm developed in 2020 [27]. Its behavior and power are effectively demonstrated on benchmark problems as compared with many approaches. Besides, TSO also solved seven different engineering problems successfully and reached much better results than others [27]. This paper nominates TSO for the ELD and MELD problems. The duty of TSO in the study is to verify the best optimal power output to reduce total costs of three test systems such as System 1 with 6 thermal units, System 2 with 20 units, and System 3 with 20 units and 2 WFs. Three systems are also solved by PSO [28] and SSD [29].

The novelties of the paper are as follows:

- Apply TSO, PSO and SSD to the problem of ELD with prohibited zone (PZs) and power losses (PLs)
- Test ability of TSO on large scale system
- Consider 24 periods for MELD problem with WFs and TPPs
- Propose the modified test system from the standard test system.

In addition, this paper offers some main contributions as follows:

- TSO can find highly effective solutions of three considered systems with smaller cost than others.
- TSO can easily handle PZs constraints.
- TSO can find valid solutions for very high dimension system.

2. FORMULATION OF STUDIED PROBLEM

2.1 Objective function

The electric power generation cost of each generating unit k (GC_k) is a convex function according to its power output and the fuel cost coefficients given [3] as follows:

$$GC_k = c_k.(P_k)^2 + b_k.P_k + a_k \tag{1}$$

where c_k, b_k and a_k are given coefficients in GC_k function.

In power system operation and management, the total fuel cost (TFC) of TPPs accounts of the amount of high share that needs to be minimalized. The objective of the ELD problem is presented as the following equation.

$$\text{TFC} = \sum_{m=1}^{24}\left(\sum_{k=1}^{NT} GC_k^m\right) \tag{2}$$

where *NT is number of* the generating units

2.2 Constraints of the Economic load dispatch problem

- *Generation limits*: power generated by units at each period must satisfy the inequality [3]:

$$P_{km,min} \le P_{km} \le P_{km,max} \tag{3}$$

where $P_{km,max}$ and $P_{km,min}$ are the highest and lowest power produced by the *kth* unit.

Violation of Prohibited zones: Power generated by each unit k at each period is constrained as the following model [14].

$$P_{km} \in \begin{cases} P_{km,min} \le P_{km} \le PL_{km,t-1} \\ PU_{km,t-1} \le P_{km} \le PL_{km,t} \quad t=2,\ldots,Nz \\ PU_{km,Nz} \le P_{km} \le P_{km,max} \end{cases} \tag{4}$$

where Nz is the number of PZs, $PL_{km,t}$ is the lower bound of the *tth PZ* of the *kth* generating unit at the *mth* period, $PU_{km,t}$ is the upper bound of the *tth PZ* of the *kth* generating unit at the *mth* period

- *Power balance constraint*: Real power balance constraint is an absolute guarantee. Wherein the total generated power side must equal the sum of consumed power side and power losses. Such constraint is given as the model below:

$$P_{wind,m}+\sum_{k=1}^{NT} P_{k,m} = CPS_m+ PLs_m,\ m=1,...,24 \qquad (5)$$

where $P_{wind,m}$ is power output of WF at the *mth* period, CPS_m is a consumed power side at the *mth* period.

3. TUNICATE SWARM OPTIMIZER

The tunicate swarm optimizer (TSO) [27] has been developed inspired by finding the food source. TSO has two search mechanisms for updating position of tunicates. One is for the tunicate with the best position; it means that the tunicate is at the food source. Another is for the remaining tunicates.

The main steps of the TSO method are explained as follows:

3.1 Initialization position

Position of all tunicates (T_n) can be randomly generated within the search spaces.

3.2 Updating position

There are two ways to update the position of the best tunicate and other tunicates.

For the best position of tunicate: Updating position of the best tunicate T_{best} depends on the location of the food source (*LFS*), the conflicts avoiding factor ω and a random number (C) [27].

$$T_{best}=\begin{cases} LFS+ \omega \times(LFS\text{-}C \times T_{best}) & if\ C \geq 0.5 \\ LFS\text{-}\omega \times(LFS\text{-}C \times T_{best}) & if\ C < 0.5 \end{cases} \qquad (6)$$

where ω is formed by

$$\omega = \frac{\varepsilon_1+\varepsilon_2\text{-}(2\times\varepsilon_3)}{lb+\varepsilon_3\times(ub\text{-}lb)} \qquad (7)$$

where ε_1, ε_2, ε_3 are three random numbers within [0, 1]; and u*b* and *lb* denote the highest and smallest speeds.

For the position of the *nth* tunicate: Updating position of the tunicates depends on the position of the best position of tunicates ($T_{(n+1)}$) and the current position of tunicates ($T_{(n)}$) [27].

$$T_{(n+1)}=\frac{T_{(n+1)} + T_{(n)}}{2+ \varepsilon_1}\ ;n=1,..,(N_p\text{-}1) \qquad (8)$$

where N_p *is* population size of tunicates

3.3 Check bound new position

The position of each tunicate is checked and adjusted in a given search space. If the obtained position of each tunicate violates one of the search spaces, this position needs to be modified so that this position must satisfy space limit.

3.4 Calculate the fitness value

Each position corresponding to a solution is evaluated to improve the obtained solution after each iteration. The fitness function for evaluating solutions is defined as below.

$$Fitness = TFC+ k\times\Delta CT \qquad (9)$$

where k is penalty and ΔCT is the value of the violated constrains.

3.5 Flowchart of the proposed Tunicate swarm optimizer

The execution of TSO method for a general optimization problem can be described in Figure 1.

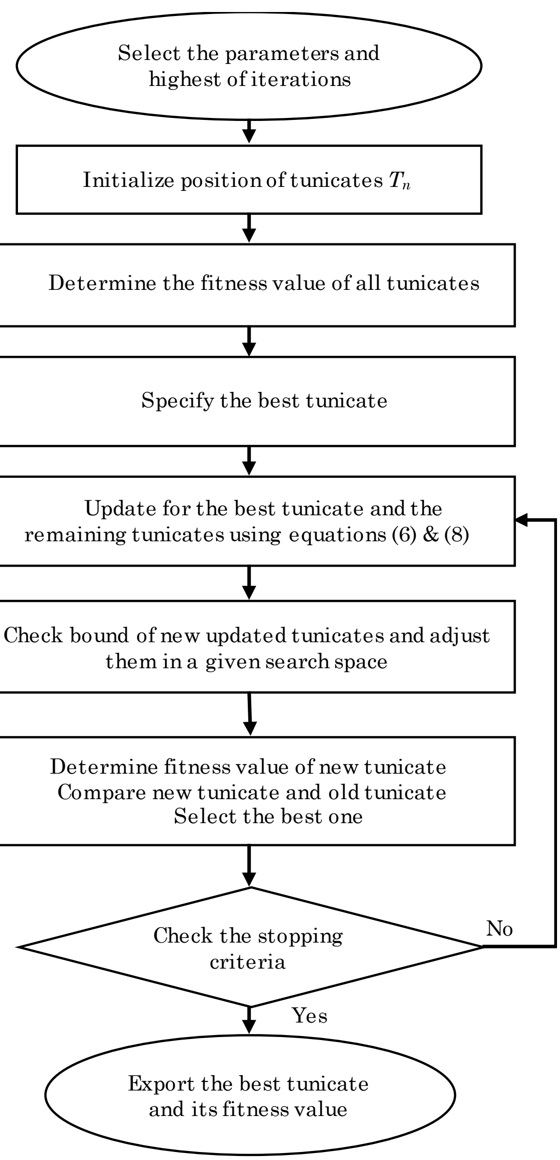

Fig. 1. Flowchart of TSO for an example problem.

4. NUMERICAL RESULTS

In this section, three systems including two standard systems and one modified system are used to assess the usefulness of TSO, PSO and SSD methods. The solutions obtained from TSO, PSO and SSD by testing on three systems are collected and compared to others. For running methods, the population (N_p) and the iterations (N_{mt}) are set as follows:

- N_p =50 and N_{mt} = 200 are respectively assigned to TSO, PSO and SSD for System 1
- N_p =50 and N_{mt} = 500 are respectively set to TSO, PSO and SSD for System 2
- N_p =50 and N_{mt} = 500 are respectively selected to TSO, PSO and SSD for System 3

For each test system, 50 trial runs are implemented for evaluating the robustness of TSO, PSO and SSD.

The whole work for coding three methods is executed on MATLAB and run on a personal PC.

4.1 Result comparisons for System 1

In this section, System 1 with 6 thermal units considering PLs and PZs is utilized to test the potentialities of TSO, PSO and SSD. Input data and B coefficients of network losses of System 1 are in [15]. The CPS of such system is 1200 MW. The obtained optimization results from TSO, PSO, SSD and other methods such as ISO [13], NAPSO [15], EMS [16], MKHS [17], and ACSS [18] are enumerated in Table 1 and displayed in Figure 2. In the table, the smallest cost (SC), average cost (AC) and highest cost (HC) of all methods are reported. Only EMS [16] did not report HC. In the consideration of SC between TSO, PSO and SSD, that of TSO is $15443.075 while that of PSO and SSD is $15443.170 and $15443.109. It shows that TSO is better than PSO and SSD. As compared to other remaining methods about SC, only four methods such as TSO, ISO [13], EMS [16] and MKHS [17] can reach the best value of $15443.075 while ACSS [18] is the worst method with $15443.556. For assessing SC, AC and HC of all methods, it can be seen that those of TSO and ISO [13] are approximately equal and better than other ones. Clearly, TSO is one of two outstanding methods for solving System 1. The convergence characteristic of TSO, PSO and SSD algorithms plotted in Figure 3 designates that TSO can obtain better solutions than PSO and SSD. In addition, the 50 runs for TSO, PSO and SSD is also collected and displayed in Figure 4. As seen in Figure 4, three curves represent the results of three methods applied in this case in which the black, blue and red curves display fitness function of 50 runs of PSO, SSD and TSO. It is quite easy to realize that the fluctuation level of the fitness value given by TSO is the lowest among three methods. TSO can find better solution quality than PSO and SSD for all the runs.

Table 1. Comparison of fuel costs of methods for System 1

Methods	SC ($)	AC ($)	HC($)
ISO [13]	15443.075	15443.077	15443.120
NAPSO [15]	15443.760	15443.766	15443.766
EMS [16]	15443.075	15443.075	-
MKHS [17]	15443.075	15443.327	15443.916
ACSS [18]	15443.556	15458.202	15490.690
PSO	15443.170	15458.856	15501.546
SSD	15443.109	15446.217	15454.380
TSO	15443.075	15443.085	15443.123

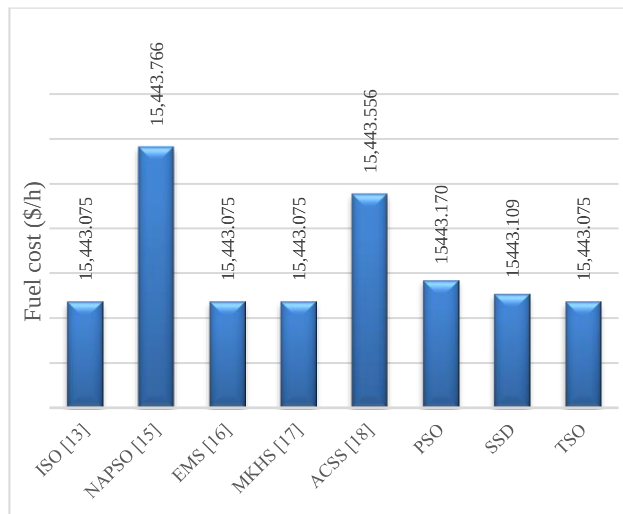

Fig. 2. The smallest cost of methods for System 1.

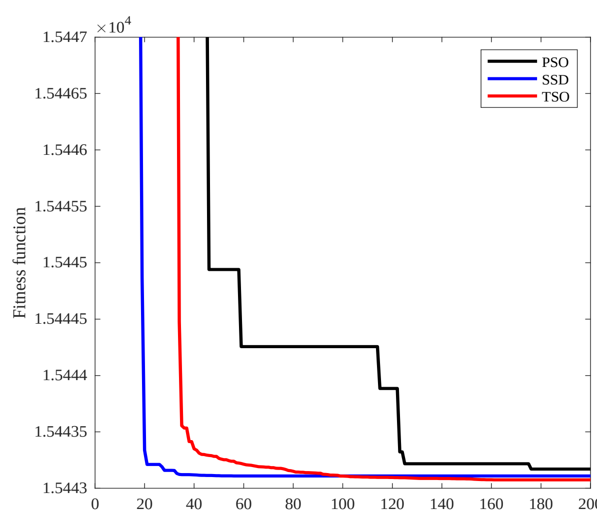

Fig. 3. The best convergence curve of TSO, PSO and SSD for System 1.

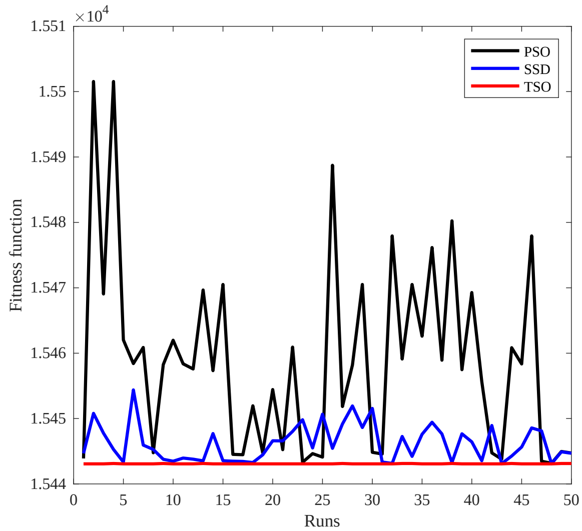

Fig. 4. The best fuel costs using TSO, PSO and SSD under 50 runs for System 1.

4.2 Result comparisons for System 2

In this section, System 2 has 20 thermal units considering PLs. Total load power of such system is 2500 MW. Input data for System 2 are taken from [9]. Figure 5 displays the smallest cost of TSO, PSO, SSD and six methods. In three applied methods, TSO again proves its outstanding ability over PSO and SSD through SC. That of TSO is \$62456.633 whilst that from PSO and SSD is respectively \$62456.876 and \$62456.664. Compared to TSO and other methods, ORCS [2], ISFS [12] can find the same SC as TSO. That of HM [1], IFO [7], and BS [9] is worse than TSO. It means that TSO is capable of solving System 2 more effectively.

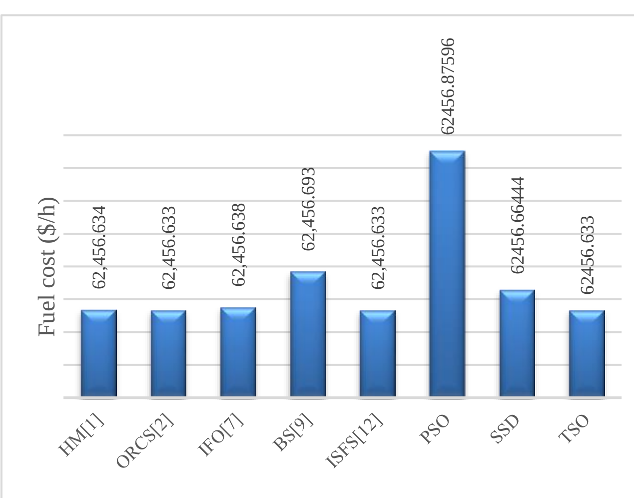

Fig. 5. The minimum fuel cost of methods for System 2.

The convergence characteristic and robust levels of TSO, PSO and SSD algorithms are plotted in Figures 6 and 7, respectively. Figure 6 depicts the search speed of TSO in red curve is faster than that of PSO in black one and SSD in blue one. From about 170th iterations, the red curve is always under black curve and blue curve. It means that TSO can reach the best solution whereas PSO and SSD can't reach. Figure 7 displays fitness values of 50 implementation runs obtained by three methods. Among the three curves, the shape of the red curve is almost unchanged while that of the black and the blue curves is a high fluctuation. From the point, it proves TSO approach is more efficient and robust than PSO and SSD.

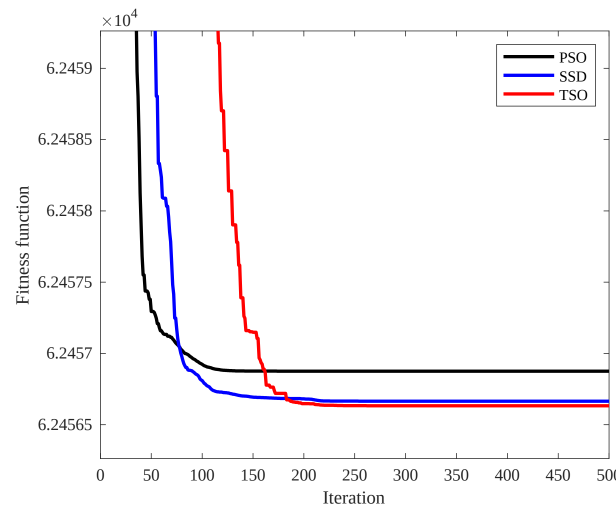

Fig. 6. The best convergence curve of TSO, PSO and SSD for System 2.

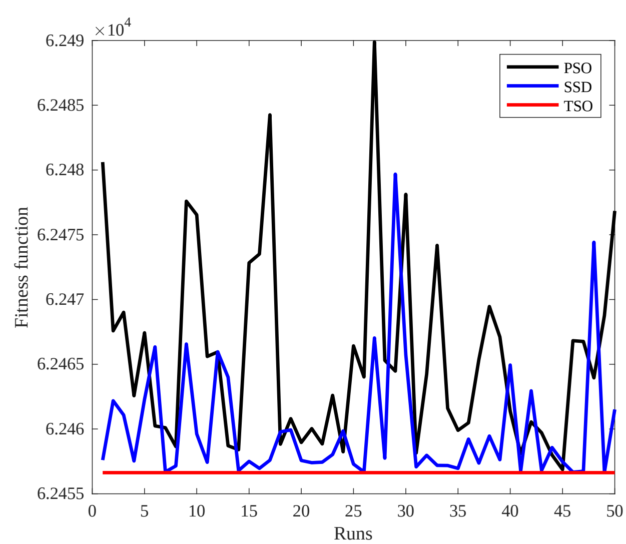

Fig. 7. The best fuel costs using TSO, PSO and SSD under 50 runs for System 2.

4.3 Result comparisons for System 3

System 3 is a modified system formed System 2. System 3 has 20 thermal units and 2 WFs. Data of thermal units of System 3 like that of System 2. The operation scheduling of TPPs and WFs are found in such system. Because velocity of wind changes continuously, power output of WF also changes accordingly. Therefore, such system will consider different CPSs corresponding to 24 periods in day. This is a big difference between System 2 and System 3. The total load demand and power outputs of wind power of each hour in a day are shown in Table 2. The minimum fuel cost by using TSO each CPS with WF and without WF is presented in Table 3. These results show that the total fuel cost with WFs is always better than that of without WFs. Total fuel cost with WFs is $1196742.156 whilst that of without WFs is $1264644.939. Figure 8 shows that the fuel cost of with WFs in orange bar is always lower than that without WFs in blue bar at each period. This demonstrates the effectiveness of wind power in minimizing fuel cost. As a result, it can lead to a conclusion system with WFs is more potential than system with only TPPs.

Optimal solutions of the systems are reported in Tables A1-A2 in Appendix.

Table 2. Consumed power side and WF power for System 3

Times	CPS (MW)	WF power (MW)	Times	CPS (MW)	WF power (MW)
1	1600	150	13	2500	150
2	1600	150	14	2500	150
3	1600	130	15	2500	150
4	1600	130	16	2500	150
5	1600	150	17	2000	150
6	1800	150	18	2000	150
7	1800	100	19	2000	120
8	2500	100	20	2000	120
9	2500	140	21	2000	120
10	2500	140	22	1500	150
11	2500	140	23	1500	150
12	2500	140	24	1500	150

5. CONCLUSION

This paper applied a new meta-heuristic proposed in early 2020 called Tunicates Swarm Optimizer (TSO) for solving both ELD and MELD problems successfully with an outstanding performance over other metaheuristic algorithms. Specifically, the ELD and MELD problems have been solved by TSO, PSO and SSD. The power of three methods was proven by testing on three systems. Among the three systems, the last one is first proposed in this paper because of the change of wind power over a day. The collected results from three methods on System 1 and System 2 are used to find the strongest method. As results, TSO is the best. TSO' results are continuously compared with other methods. As a result, it proves that TSO is a promising method. From the analysis results on System 3, it shows that the system with wind power has better total fuel cost than the system without wind power.

The paper showed the robustness of TSO and it promised that TSO or its modified versions can be more effective for the problems or other problem in power systems. For instance, ELD with more complicated constraints such as valve point effects [11] and multi fuel options [12] will be solved in the future by TSO or other proposed modified TSO.

Table 3. Cost obtained from TSO of System 3 with and without WFs

Times	Total fuel cost without wind power ($/h)	Total fuel cost with wind power ($/h)
1	43995.560	41003.879
2	43995.561	41003.879
3	43995.560	41400.941
4	43995.560	41400.941
5	43995.560	41003.879
6	48028.349	44999.630
7	48028.340	46006.649
8	62456.633	60365.876
9	62456.633	59532.356
10	62456.633	59532.356
11	62456.633	59532.355
12	62456.633	59532.356
13	62456.633	59324.226
14	62456.633	59324.225
15	62456.633	59324.225
16	62456.633	59324.225
17	52101.583	49042.912
18	52101.584	49042.916
19	52101.584	49652.847
20	52101.583	49652.848
21	52101.584	49652.851
22	41997.611	39028.594
23	41997.611	39028.594
24	41997.611	39028.594
Total	1264644.939	1196742.156

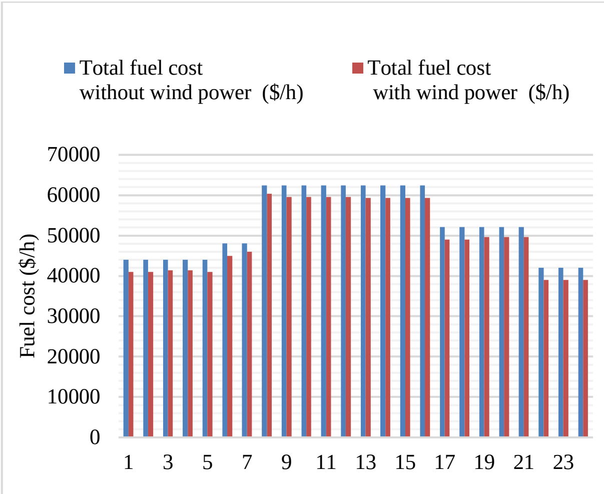

Fig. 8. Cost obtained from TSO for each period of System 3 with and without WFs.

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APPENDIX

Table A1. Optimal solution of TSO and other compared methods of System 1

Unit (MW)	ISO [13]	NAPSO [15]	EMS [16]	MKHS [17]	ACSS [18]	TSO
P_1	447.399	446.423	447.387	447.399	440.131	447.413
P_2	173.241	172.608	173.252	173.241	174.706	173.196
P_3	263.382	262.618	263.372	263.382	261.650	263.405
P_4	138.980	142.775	138.989	138.981	139.296	138.963
P_5	165.392	164.665	165.365	165.391	172.531	165.432
P_6	87.052	86.323	87.078	87.052	87.154	87.036
Total generation (MW)	1275.445	1275.413	1275.444	1275.446	1275.468	1275.446
Loss (MW)	12.445	12.413	12.443	12.446	12.468	12.446
Total cost ($)	15443.075	15443.770	15443.075	15443.075	15443.556	15443.075

Table A2. Optimal solution of TSO and other compared methods of System 2

Unit (MW)	HM [1]	ORCS [2]	BS [9]	ISFS [12]	TSO
P_1	512.780	512.776	510.448	512.793	512.782
P_2	169.104	169.114	168.397	169.308	169.101
P_3	126.890	126.880	125.972	126.877	126.891
P_4	102.866	102.858	103.529	102.852	102.867
P_5	113.684	113.680	113.821	113.638	113.683
P_6	73.571	73.569	73.790	73.549	73.572
P_7	115.288	115.279	115.066	115.292	115.290
P_8	116.399	116.389	116.340	116.440	116.400
P_9	100.406	100.408	100.709	100.389	100.405
P_{10}	106.027	106.047	107.137	105.827	106.027
P_{11}	150.240	150.241	150.706	150.216	150.239
P_{12}	292.765	292.785	291.130	292.792	292.766
P_{13}	119.116	119.115	119.153	119.173	119.114
P_{14}	30.824	30.842	32.452	30.841	30.832
P_{15}	115.806	115.823	116.148	115.841	115.806
P_{16}	36.255	36.263	36.282	36.244	36.254
P_{17}	66.859	66.846	67.736	66.842	66.859
P_{18}	87.972	87.960	87.255	88.017	87.971
P_{19}	100.803	100.791	101.536	100.790	100.803
P_{20}	54.305	54.307	54.286	54.310	54.305
Total generation (MW)	2591.893	2591.970	2591.893	2592.029	2591.967
Loss (MW)	91.967	91.970	91.893	92.029	91.967
Total cost ($)	62456.634	62456.633	62456.693	62456.633	62456.633

[28] Kennedy, J., & Eberhart, R. (1995, November). Particle swarm optimization. *In Proceedings of ICNN'95-International Conference on Neural Networks* (Vol. 4, pp. 1942-1948). IEEE.

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