DYNAMIC ECONOMIC LOAD DISPATCH PROBLEMS IN MICROGRID CONTAINING RENEWABLE ENERGY SOURCES BASED ONTUNICATE SWARM ALGORITHM

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Abstract:

Dynamic Economic Load Dispatch (DELD) is a significant problem in microgridincluding renewable energy sources (RESs).The aim of this paper is to minimize the overall cost of the system while ensuring that the power demands of the consumers are met. However, with the added complexity of RESs, conventional optimization techniques may not be able to provide optimal solutions. This is where metaheuristic algorithms come into play, which are optimization techniques inspired by natural phenomena such as biological, nature, and animal behavior. This studycovers a new bio-inspired algorithm called Tunicate Swarm Algorithm (TSA)applied for solving DELD in microgrid with considering the variable power output of RES such as wind and solar energy. The DELD problem should also incorporate various constraints such as power balance and generation limits. Four cases of DELD containing RESs are treated. The obtained resultsare compared to other methods.. The result shows that for the DELD problem, the TSA demonstrate the superiority in term of optimise thegeneration cost compared to other optimization techniques.

1 Introduction

DELD problems are increasingly relevant in modern power systems due to rising renewable energy penetration and fluctuations in demand [1]. They aim to determine the optimal generation schedule for committed units over a time horizon, minimizing operating cost while considering real-time changes in load and system constraints.

Microgrid is defined as a set of distributed energy resources (DERs), containing RESs and energy storage systems (ESS), and loads that operate locally as a single controllable entity [2]. Among them, the economic factor, which is mainly related to the DELD problem[3], is at the center of many power system operation problem [4]. In the literature, many modeling techniques can be adopted and presented to solve the complex problem of DELD successfully.

Mousumi Basu in [5], recommends chaotic fast converging evolutionary programming (FCEP), rooted in the provisional equation, to solve the DELD problem involving RESsand pumped hydro energy storage. C. Shilaja in Ref.[6], proposed a new method called euclidean affine flower pollination (EAFP)algorithm and binary flower pollination algorithm (BFPA) based on the combination of economic emissions dispatch (EED) for thermal energy production units and photovoltaic plants to optimize the economic dispatch problem. For instance Ref.[7],W. Sheng studied the problem of a hybrid dynamic EED(DEED) with DERs using improved COOT optimization algorithm.In the literature [8], Multi-objective DEED with RESs and electrical vehicle using equilibrium optimizer are presentedto optimize the total operating cost of the system.In addition [9], proposes a DELD scheme for isolated microgrids incorporating demand response through price incentives and

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particle swarm optimization for efficient dispatch. To reduce the operating cost and the pollutant emission targets[3], addresses a microgrid connected to the main grid, considering uncertainties in demand, renewable generation, and market prices. It employs a PSO algorithm for DELD while incorporating environmental objectives and demand response programs. In addition, for efficient and scalable dispatch [10], focuses on a decentralized DELD approach for microgrids with communication limitations and uncertainties by applied a distributed alternating direction method of multipliers (ADMM) algorithm.

DELD in microgrids with various resource integration is a crucial aspect of optimizing energy management in these complex systems[11]. It involves strategically distributing the time-varying electrical load demand among different available resources within the microgrid[12], considering multiple factors such as resource types (wind, PV, diesel engines, and ESS), maximizing RES utilization, maintaining power quality, and ensuring system stability[13], [14].In [15], experts have explored the optimization of DERs and battery storage considering cost, emissions, and reliability with an enhanced GWO algorithm. For studied DELD in microgrid, [16] proposed a hybrid scheme combining GA and PSO while considering battery storage, demand response, and uncertainty in renewable generation.

Integration of machine and deep learning to solve the DELD problem for microgrids considering RESs has become the research hotspot[17]. For example [18], incorporates deep learning for forecasting and real-time DELD in microgrids with uncertainties. Hence, [19], utilizes deep reinforcement learning based DELD for microgrids with battery storage.Furthermore, for demand response integration within DELD, and enhancing flexibility and cost-effectiveness in microgrids with RESs, authors have proposed Q-learning technique[20].

In this study, a new optimal dispatch algorithm for units considering RESsaccess is suggested, considering conditions such as variable power output of wind and PV energy and unit power balance and generation limits.

In order, to address these problems, this work investigates this problem of optimizing the DELD of island microgrid by combining thermal unit, wind and PV.The contributions of this study are as follows.

- Tunicate Swarm Algorithm (TSA)is introduced into this model to address the complexity of the problems in system optimization.
- The validation of the DELD model in a 3-unit system containingwind and PV, proves that the TSA has achieved favorable results in terms of operation cost compared to other methods, thus having satisfying practical value.

The remainder of this study is organized as follows.Section 2 develops the DELD model including thermal, wind and PVsystems. The TSA is described in depth in Section 3. In section 4, a 3-unit test system with diffrent combinations of RES isused to analyze and check the best results of the proposed models. Finally, Section 5 summarizes the main points of this research and gives an outlook for future work.

2 Mathematical Model

We consider a power system supplied by a set of power plants each having several machines. The cost of the fuel necessary for the production of electric power for each machine is a monotonic function of the power demanded [21].

2.1 Presentation of the objective function

In the problem of economic dispatching, the objective function to be minimized is the total production cost of the thermal groups. The curves giving the production cost of each unit (in $/h or MBtu/h) according to the power it delivers in (MW) were determined experimentally [22], [23].

Each unit will produce its own power according to a convex cost function given by the following quadratic function [24]:

$$F_i(P_i) = u_i P_i^2 + v_i P_i + w_i \tag{1}$$

where$F_i(P_i)$ is the fuel cost of i^{th}generator with output P_i, the cost coefficients u_i,v_i and $w_i$corresponding of generator $i$are numerically known.

For the minimization of operating cost of generators, the objective function is [25]:

$$Min\ \ F_T = \sum_{i=1}^{NG} F_i(P_i) \tag{2}$$

where F_T is the total generation cost in (\$/h) while meeting the load demand, and NG is the number of generating units.

2.2 Formulation of DELD problem

DELD problems are particularly challenging because they involve complex nonlinear functions, non-convex constraints, and time-varying loading conditions. In addition, the solution must be obtained in real-time to ensure the stability and reliability of the power system.

Themathematical formulation for the DELD problem can be expressed as follows[1], [25]:

$$Min\ \ F_T = \sum_{t=1}^{24}\sum_{i=1}^{NG}\{u_i P_i^2(t) + v_i P_i(t) + w_i\} \tag{3}$$

where $P_i(t)$ is rated output power produced by generator i at hour t.

2.3 Isolated microgrid in the presence of RESs:

The total cost of production can be reduced by the integration of RESs for the generation of power. In this study, the optimization objectives of operating cost of an isolated microgrid by combining thermal unit, wind farms and PV systems is discussed. The cost of RESs includes investment cost, operationaland maintenance (O&M) costs can be computed as follows: [27, 28]:

$$F(P_{RES}) = P_{RES}[AC.I^P + G^E] \tag{4}$$

where P_{RES} is the output power of the RESs in(KW), AC is theannuitization coefficient, I^P is the ratio of investment cost to unit installed power in (\$/kW) and G^E is the O&M costin (\$/kW).

Annuitization coefficient can be determined as below:

$$AC = \frac{r}{[1-(1+r)^{-N}]} \tag{5}$$

where r is the interest scale and N is the investment duration in years.

The O&M cost for the wind and PV (G^E)is 0.016\$/kW, invested at 9% interest scale for 20 years[26]. The I^P cost to establish powerfor PV andwind is 5000\$/kW and 1400\$/kW respectively[26].Thus, the costfunction of PV plants and wind becomes $547.7483 \times P_{PV}$ and $153.3810 \times P_{wind}$ respectively [27].

Therefore, with the integration of PV and wind, Eq. (3)becomes:

$$Min\ \ F_T = \sum_{t=1}^{24}\sum_{i=1}^{NG}\{u_i P_i^2(t) + v_i P_i(t) + w_i\} + 547.7483 \times P_{PV}(t) + 153.3810 \times P_{wind}(t) \tag{6}$$

The objective function (6) is subject to the following constraints:

i. *Generator operating limits*: The power produced by the thermal units as well as the RESs must lie between an upper and lower limit. Mathematically,

$$P_i^{min} \le P_i \le P_i^{max} \tag{7}$$

$$P_{RES}^{min} \le P_{RES} \le P_{RES}^{max} \tag{8}$$

where P_i^{min} and P_i^{max} indicates the minimum and the maximum power limits of i^{th} thermal unit respectively. P_{RES}^{min} and P_{RES}^{max} are respectively the lower and upper boundary power of RESs.

ii. *Power balance constraint*:

$$P_{Load} = P_i + P_{RES}, i = 1,2,\dots,NG \tag{9}$$

This study focuses on minimizing Eq. (6) using TSA and a comparative study among the methods as well as the minimized costs of ELD.

3 Tunicate swarm algorithm TSA

The standard tunicate swarm algorithm is a very simple bio-inspired metaheuristic optimization technique, which was first proposed by S. Kaur et al. in 2020 [28]. Its inspiration and performance were proven over the seventy-four benchmark problems compared to several other optimization approaches. Its efficacy and unpretentious structure draw the attention to employ and improve this algorithm for the considered problem. The swarm behavior of TSA is given in Figure 1[29]. TSA main limitates the swarming behaviors of the marine tunicates and their jet propulsions during its navigation and foraging procedure [30].

In TSA, a population of tunicates (PT) is swarming to search for the best source of food (SF), representing the fitness function. In this swarming, the tunicates update their positions related to the first best tunicates stored and upgraded in eachiteration. The TSA begins where the tunicate population is initialized randomly, considering the permissible bounds of the control variables. The dimension of the control variables composes each tunicate (T),whichcan be initially created as [31].

$$T_n(m) = T_{min}^n + r \times (T_{max}^n - T_{min}^n) \quad \forall m \in PT_{size} \,\&\, n \in Dim \tag{10}$$

Where $T(m)$ stands for the position of each tunicate (m); n refers to each control variable in dimension Dim; r is a random number within the range (0:1); and PT_{size} indicates the number of tunicates in the population.

The update process of the tunicates position is executed by the following formula [28]:

$$T_n(m) = \frac{T_n^*(m) - T_n^*(m-1)}{2 + c_1} \tag{11}$$

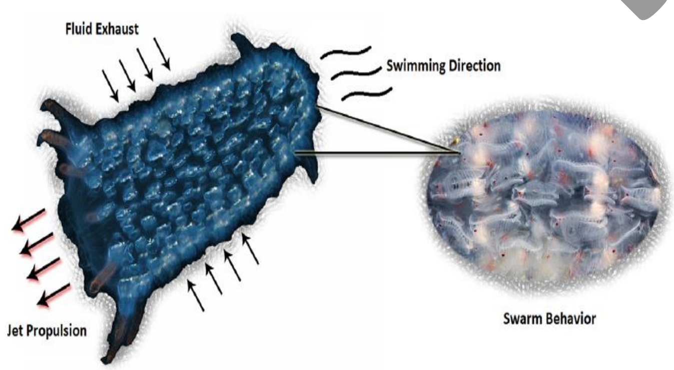

Figure1.Inspiration of TSA[28].

whereT^*denotes the updated position of the m^{th}tunicate based on Eq. (11);$T(m-1)$refers to the neighbor tunicate; c_1 is a random number, uniformly distributed between 0 and 1.

$$T_n^*(m) = \begin{cases} SF + A \times |SF - rand \times T_n(n)| if rand \geq 0.5 \\ SF - A \times |SF - rand \times T_n(n)| if rand < 0.5 \end{cases} \tag{12}$$

where $SF$is the source of food, which is represented by the best tunicate position in the whole population; A is a randomized vector to avoid any conflicts between tunicates and each other, which is expressed as[29]:

$$= \frac{c_2 + c_3 - 2c_1}{VT_{min} + c_1(VT_{max} - VT_{min})} \tag{13}$$

wherec_2 and $c_3$are random numbers within the range (0:1); VT_{min} and VT_{max}represent the initial and subordinate speeds to produce social interaction.

The TSA method's key steps can be described as [30]:

Step 1: Create the initial tunicate population.
Step 2: Determine the control units of TSA and stopping criteria.
Step 3: Compute the fitness values of the initial population.
Step 4: Select the position of the tunicate with the best fitness value.
Step 5: Create the new position for each tunicate by using Eq.(11).
Step 6: Update the position of the tunicatesthatare out of the search space.
Step 7: Compute the fitness values for the new positions of tunicates.
Step 8: Until stopping criteria is satisfied,repeat steps 5–8.
Step 9: After stopping criteria is satisfied, save the best tunicate position.

The flowchart of TSA for ELD problem is display in figure 2.

4 Simulation results and discussion

4.1 *Description of the system*

In order to evaluate the robustness and the efficiency of the proposed TSA in solving DELD problems, the test system is an isolated microgrid (fig. 3) consisting of 3-thermal units,one PV of 40 MW, and one wind of 30 MW[27]. Four case studies have been taken into consideration. The constraints involved are power balance constraints and generator operating limits constraint. The obtained results are compared with these obtained by other optimization approaches recently published in the literature. DELD with four combination include:

- Case I: DELD problem of 3-units system without both PV andwind.
- Case II: DELD problem of 3-units system with wind.
- Case III: DELD problem of 3-units system with PV.
- Case IV: DELD problem of 3-units system with all RESs.

The TSA was applied to solve DELD problem for all cases studies in MATLAB R2017a, under windows 8.1 on Intel Core i5 CPU 2.60 GHz,with 8.0 GB RAM. The TSA program for all combination is executed with 50 population and 1000 iterations. While performing TSA, the initial and subordinate speeds$VT_{min}$and VT_{max}were 1 and 4 respectively. The values of these parameters are determined after performing various experiments, which provide more exploratory power.The operating ranges, cost coefficients of the thermal generators are depicted in Table 1.

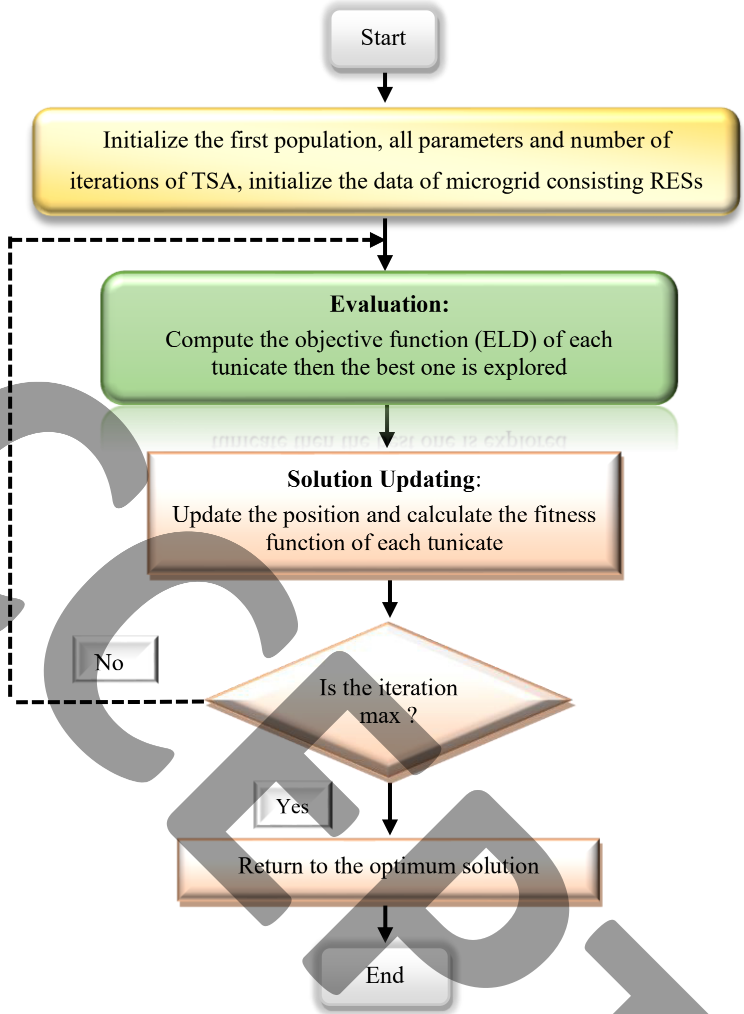

Figure 2. flowchart diagram of the TSA for ELD.

The 24 h output powers of PV and wind are estimated for a range of solar radiation and wind speed at a site on the east coast of USA [27] and are displayed in Table 2 along with the hourly load demand of the microgrid.

Table 1. Generator power limits and cost coefficients of 3-unit power system [27]

Parameters	Generator 1	Generator 2	Generator 3
u	0.0024	0.0029	0.0210
v	21.00	21.16	20.40
w	1530	992	600
P_{min} (MW)	37	40	50
P_{max} (MW)	150	160	190

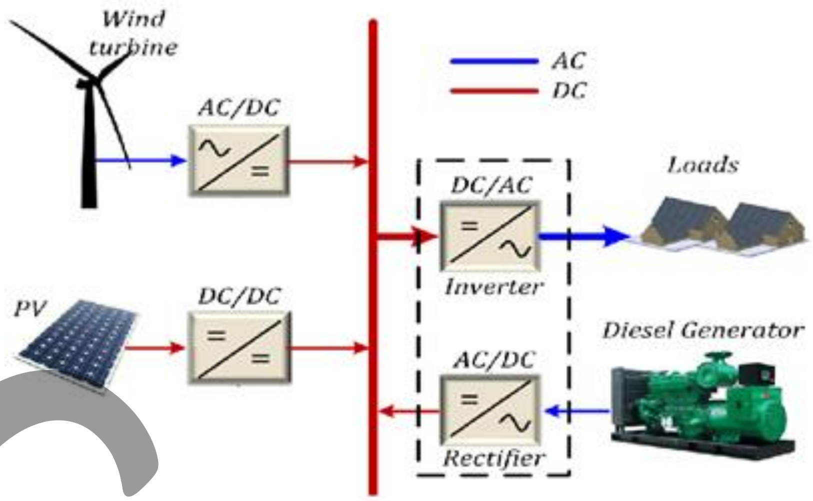

Figure 3. Architecture of an isolated microgrid[32].

Table 2.Day ahead forecasted hourly output of wind and PV and hourly load demand in (MW)

Hour (h)	P_{wind}	P_{pv}	P_{Load}	Hour (h)	P_{wind}	P_{pv}	P_{Load}
1	1.70	0	140	13	14.35	31.94	240
2	8.5	0	150	14	10.35	26.81	220
3	9.27	0	155	15	8.26	10.08	200
4	16.66	0	160	16	13.71	5.3	180
5	7.22	0	165	17	3.44	9.57	170
6	4.91	0.03	170	18	1.87	2.31	185
7	14.66	6.27	175	19	0.75	0	200
8	25.56	16.18	180	20	0.17	0	240
9	20.58	24.05	210	21	0.15	0	225
10	17.85	39.37	230	22	0.31	0	190
11	12.8	7.41	240	23	1.07	0	160
12	18.65	3.65	250	24	0.58	0	145

4.2 Comparative Analysis

The operating costs associated with performing DELD on the islanded microgrid test system for different scenarios utilizing TSA are listed in Table 3. It is evident that TSA achieved better and more favorable results thanPSO, DE, SOS, GWO and WOA in each of the four different combination of varying power demands. For the cases of « without all RESs »,« with wind », « with PV », and « with all RESs »,TSA incurred the following costs: \$162596.3346, \$203188.0930, \$270682.6897, and \$297385.567, respectively. For the previously indicated cases, these obtained values represent the lowest cost that might be achieved by the compared methods. It is also to be noted that the maximum costs when we used PV system compared with wind energy.

Table 3.Comparison of microgrid cost (in \$) for DELD with different techniques.

Algorithm	Case 1	Case 2	Case 3	Case 4
PSO[27]	176177.9174	204025.1856	272045.2086	299919.4357
DE[27]	176169.0719	204006.9307	272036.3530	299916.0487
SOS[27]	176168.0424	204001.6485	272034.5209	299906.3846
GWO[27]	176167.8827	203988.3084	272033.5531	299896.6562
WOA[27]	176166.5662	203987.5104	272031.0549	299895.7531
TSA	162596.3346	203188.0930	270682.6897	297385.567

Hourly outputs (in MW) of conventional generators for DELD using TSA (case I) are illustrate in Table 4.

Table 4.Hourly outputs (in MW) of 3-thermalunits for DEED using TSA (case I).

Hours	ELD	P_{G1}	P_{G2}	P_{G3}
1	6367,226	39,4976	48,403	50.000
2	7465,770	49,117	42,109	50.000
3	7664,121	38,049	57,530	50.000
4	8731,630	37.000	56,341	50.000
5	7587,914	63,120	44,660	50.000
6	7444,630	72,700	41,960	50.000
7	12111,221	61,911	41,884	50.000
8	18864,833	39,406	48,704	50.000
9	22975,645	53,453	61,916	50.000
10	31103,542	77,326	45,454	50.000
11	13893,351	45,706	123,687	50.000
12	12868,768	130,363	47,064	50.000
13	26965,576	74,052	69,504	50.000
14	23289,124	79,264	53,576	50.000
15	13779,482	80,892	50,768	50.000
16	11595.000	70,588	40.000	50.000
17	12260,860	64,146	42,570	50.000
18	8540,575	90,671	40.000	50.000
19	7489,585	63,465	85,783	50.000
20	8273,934	85,801	104,030	50.000
21	8007,089	48,576	120,500	50.000
22	7241,732	66,573	72,841	50.000
23	6685,627	57,579	51,202	50.000
24	6285,104	54,419	40.000	50.000

Table 5 list the hourly output of the thermal generatorsfor case II when DEED was evaluated using TSA. Test case IV becomes more complex than the three cases studied above. The best statistical results of TSAare recorded in Table 7.

Table 5.Hourly outputs (in MW) of 3-thermalunits for DEED using TSA (case II).

Hours	ELD	P_{G1}	P_{G2}	P_{G3}
1	6312.176	37.001	52.998	50.001
2	7560.125	37.000	62.999	50.001
3	7780.932	37.005	67.995	50.001
4	9017.288	37.001	72.999	50.001
5	7672.326	37.002	77.998	50.000
6	7421.154	37.000	83.000	50.000
7	9019.918	37.000	87.999	50.001
8	10795.224	37.001	92.999	50.000
9	10654.927	37.002	122.998	50.000
10	10654.826	37.001	142.999	50.000
11	10090.433	37.003	152.997	50.000
12	11198.737	40.001	159.999	50.000
13	10328.171	37.001	152.999	50.000
14	9294.861	37.001	132.998	50.000
15	8556.835	37.002	112.998	50.000
16	8977.609	37.000	92.998	50.002
17	7195.687	37.000	82.998	50.001
18	7265.154	37.000	97.999	50.000
19	7404.940	37.001	112.999	50.000
20	8153.232	37.000	153.000	50.000
21	7835.107	37.000	137.999	50.000
22	7129.594	37.001	102.999	50.000
23	6626.044	37.001	72.998	50.000
24	6242.795	37.002	57.998	50.000

Table 6.Hourly outputs (in MW) of 3-thermal units for DEED using TSA (case III).

Hours	ELD	P_{G1}	P_{G2}	P_{G3}
1	6051.430	37.000	53.000	50.000
2	6256.384	37.002	62.998	50.000
3	6359.081	37.005	67.995	50.000
4	6461.934	37.000	72.999	50.000
5	6564.921	37.001	77.999	50.000
6	6684.514	37.003	82.997	50.000
7	10205.720	37.001	87.999	50.000
8	15737.321	37.001	92.998	50.001
9	20671.714	37.000	122.999	50.001
10	29481.830	37.002	142.998	50.000
11	12185.971	37.002	152.998	50.000
12	10337.464	40.004	159.996	50.000

Hours	ELD	P_{G1}	P_{G2}	P_{G3}
13	25622.234	37.004	152.996	50.000
14	22392.499	37.002	132.998	50.000
15	12811.200	37.001	112.998	50.001
16	9777.844	37.004	92.996	50.000
17	11909.998	37.001	82.998	50.001
18	8243.625	37.002	97.998	50.001
19	7289.902	37.001	112.999	50.000
20	8127.174	37.001	152.999	50.000
21	7812.104	37.000	137.999	50.000
22	7082.055	37.003	102.997	50.000
23	6461.931	37.001	72.999	50.000
24	6153.840	37.000	57.999	50.001

Table 7.Hourly outputs (in MW) of 3-thermal units for DEED using TSA (case IV).

Hours	ELD	P_{G1}	P_{G2}	P_{G3}
1	7684,770	47,900	40.000	50.000
2	8757,480	51,225	40.000	50.000
3	8927,570	55,580	40.000	50.000
4	10008.000	53,339	40.000	50.000
5	8835,910	66,930	40,851	50.000
6	8702,090	67,690	46,970	50.000
7	13357,300	63,795	40.000	50.000
8	20180.000	48,110	40.000	50.000
9	24233,900	69,373	45,107	50,8899
10	32382,700	72,014	50,764	50.000
11	15390.000	77,700	69,521	72,1678
12	14445,200	77,479	73,329	76,6198
13	28325,700	72,9683	66,554	54,0366
14	24603,500	74,708	58,132	50.000
15	15088,800	72,525	59,133	50.000
16	12846,700	68,411	42,177	50.000
17	13507,800	65,867	40,847	50.000
18	9849,240	72,485	56,722	51,4579
19	8880,200	73,784	70,461	55,0038
20	9943,460	77,493	80,148	82,1884
21	9536,730	78,211	77,785	68,4508
22	8581,260	72,535	62,343	54,5358
23	7933,450	65,287	43,493	50.000
24	7558,810	54,419	40.000	50.000

Tables4-7 shows the hourly capacity of conventional generators for DELD with different combination of RESs using TSA. All obtained values are said to satisfy the equality and inequality constraints. During the first and last hours of low load demand, the generator will produce the minimum power required to meet demand. However, during peak periods of high demand, thermal units have been shown to provide maximum output compared to the rest of the timeframe. These values are much higher if RESs are not considered.

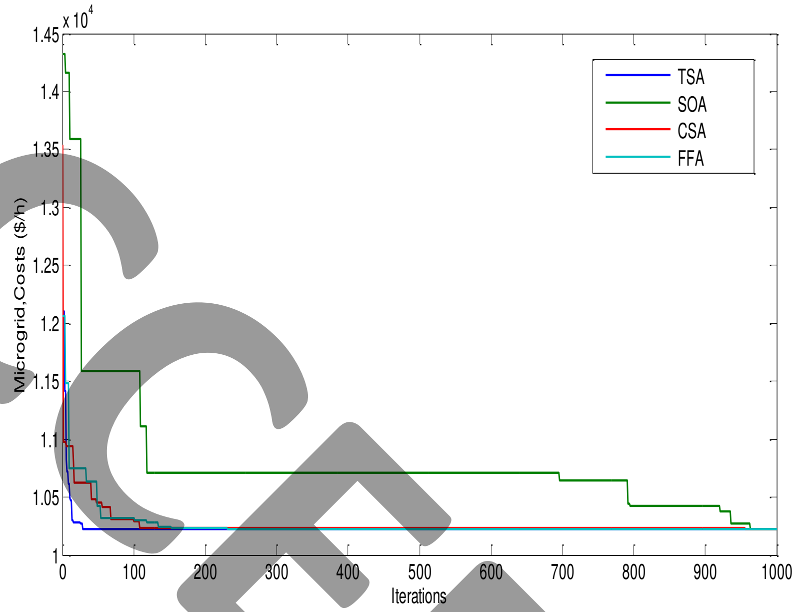

Figure 3.Total cost curve at the load = 250 MW for case I.

Figure. 4 shows the best convergence behaviors of TSA. From figure 4, it is observed that TSA converged to the optimum cost from 32 iteration; it is quickly faster than SOA[32], CSA[32], and FFA[32]. By analyzing the convergence curve, we show that TSA has fast and has better convergence with earlier iterations than CSA, SOA and FFA algorithms.

5 Conclusion

The solution of the DELD problem with RESs is critical for the economic and reliable operation of the power system. TSA has been proposed for solving the DELD problem for different combination of RESs, ranging from classical optimization algorithms to metaheuristic algorithms. Among these techniques, the TSA has shown promising results for solving the DELD. However, the selection of the appropriate solution technique depends on the size and complexity of the power system, and it is an active area of research for power system optimization.

The results obtained by applying the algorithm of the search for tunicate to the problems of the flow of power known as the economic dispatch and by taking into account the investment costs of renewable energies are very convincing and show that they have a strong applicability to solving these problems. These results are also comparable with other results obtained in the same field and satisfy.

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