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Solving the Renewable Energy Integrated Economic Load Dispatch Problem Incorporating Multiple Fuel Options of Thermal Generating Source Triangulation Topology Aggregation Optimizer

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Abstract*— This study presents the application of novel meta-heuristic algorithms, including Arctic puffin optimization (APO) and Triangulation topology aggregation optimizer (TTAO), to solve the renewable energy integrated economic load dispatch (RE-ELD) problem. The main purpose of the whole study is to determine the optimal allocation of all thermal generating sources (TGUs) in the given system so that the overall fuel expenditure is minimized. Besides, the power loss and the multiple fuel constraints of TGUs are also evaluated during the process of solving the considered problem. The results achieved by the two applied algorithms show that TTAO is better than APO in all comparison criteria, including Minimum OEF (Min. OEF), average OEF (Aver. OEF), and Maximum OEF (Max. OEF). Particularly, TTAO is more cost-effective than APO, which is $0.16 in Min. OEF, $0.722 in Aver. OEF, and $0.1794 in Max. OEF. Moreover, TTAO also proves itself to be more stable while dealing with the considered problem than APO, with lower fluctuations among trial tests. Based on all these arguments, TTAO deserves a highly effective computing method, and the algorithm is highly recommended for solving such a RE-ELD problem.*

Keywords*— Solar energy, wind energy, multiple fuel options, Arctic puffin optimization, Triangulation topology aggregation optimizer, Renewables energy integrated – economic load dispatch.*

I. INTRODUCTION

Economic Load Dispatch (ELD) still plays a key role in power system operation [1]. The main purpose of solving the ELD problem is to optimize the allocation of power generation for all thermal generating units (TGUs) in the given system so that the overall fuel expenditure (OFE) is minimal and satisfies system load demand and other constraints [2]. Besides economic benefits, optimal ELD solutions also contribute to environmental sustainability by reducing emissions from fossil fuel-based power generation [3]. Traditionally, TGUs have been the primary sources of electricity. However, the increasing integration of renewable energy sources like solar and wind power has necessitated a shift towards renewable energy economic load dispatch (RE-ELD) [4-5]. This approach involves the coordinated optimization of both conventional and renewable energy sources to achieve cost-effective and environmentally friendly power generation.

By deeply acknowledging the importance of solving ELD and RE-ELD, many researchers have published their research solving these two problems. More importantly, meta-heuristic algorithms are the most selected methods for dealing with these problems. The implementation of meta-heuristic algorithms to solve ELD and RE-ELD can be listed as Modified Jaya algorithm (MJA) [6], Modified moth swarm algorithm (MMSA) [7], Improved bacterial foraging algorithm (IBFA) [8], Fire hawk optimization (FHO) [9], Equilibrium optimizer (EO) [10], Social optimization algorithm (SOA) [11], Harmonic search algorithm [12], Salp swarm optimization (SWO) [13], Grasshopper optimization algorithm (GOA) [14], the multi-objective multi-verse optimization (MOMVO) [15], Adaptive cuckoo search algorithm (ACSA) [16], Firework algorithm (FWA) [17], Marine predator optimization algorithm (MPA) [18].

In this study, two novel meta-heuristic algorithms, including Arctic puffin optimization (APO) [19] called Triangulation topology aggregation optimizer (TTAO) [20], are applied to solve the RE-ELD problem. The main purpose of the whole study is to determine the optimal allocation of all the TGUs in the given power system so that the overall fuel expenditure (OEF) is minimal. Besides, the contribution of renewable energy sources such as solar and wind energy is also taken into account. Regarding applied algorithms, APO is proposed based on the survival and predation behaviors of the Arctic puffin, while TTAO is inspired based on the iterative evolution of vertexes, which are constantly generated in the search space and used to constitute similar triangles of different sizes.

The main novelties and important contributions of the whole paper are shortly listed as follows:

- Successfully apply two novel meta-heuristic algorithms, Triangulation topology aggregation optimizer and Arctic puffin optimization, to solve the RE-ELD problem with the consideration of multiple fuel options and power loss.
- Indicated the better-applied method, TTAO, which is more cost-effective than APO using particular evidence and discussions.
- Considering the contribution of both solar and wind energies while solving the RE-ELD problem.

II. PROBLEM FORMULA

2.1. The main objective function

The main objective function of the whole research is to minimize the overall fuel expenditure (OFE) of all the thermal generating units (TGUs) in the given power system as formulated as follows:

$$Minimize\ OFE = \sum_{n=1}^{N_{TGUs}} a_n PTG_n^2 + b_n PTG_n + c_n \quad with\ n = 1, \dots, N_{TGUs} \tag{1}$$

Where OFE is the overall fuel expenditure of all the TGUs in the given power system; a_n, b_n, and c_n are, respectively the fuel utilizing factor of the TGU n; PTG_n is the power output generated by TGU n; and N_{TGUs} is the number of TGUs in the given power system.-

2.2 The involved constraints

- *The multiple fuel constraints of TGU*

As mentioned earlier, this research will evaluate the multiple fuel constraint of each TGU, and the mathematical expression of the constraint is given below:

$$TFC = \begin{cases} a_{n,1} + b_{n,1}PTG_n + c_{n,1}PTG_n^2; & \text{if } PTG_n^{low} \le PTG_n \\ a_{n,2} + b_{n,2}PTG_n + c_{n,2}PTG_n^2; & \text{if } PTG_n^{2,low} \le PTG_n \\ \dots & \\ a_{n,m} + b_{n,m}PTG_n + c_{n,m}PTG_n^2; & \text{if } PTG_n^{m,low} \le P \end{cases} \tag{2}$$

Where $a_{n,1}$, $b_{n,1}$ and $c_{n,1}$ are respectively, the fuel utilization factor of the TGU n, PTG_n^{low} and $PTG_n^{1,high}$ are, respectively the minimum and maximum power output generated by TGU n using fuel type 1. Similarly, $a_{n,2}$, $b_{n,2}$ and $c_{n,2}$ are, respectively the fuel utilization of the TGU n using fuel type 2. $PTG_n^{2,low}$ and $PTG_n^{2,high}$ are, respectively, the minimum and maximum power output generated by TGU n using fuel type 2. And finally, $a_{n,k}$, $b_{n,k}$ and $c_{n,k}$ are, respectively the fuel utilization factor of the TGU n using fuel type k of TGS n; $PTG_n^{k,low}$ and PTG_n^{high} respectively, the minimum and maximum power output generated by TGU n using fuel type m, with m is denoted as the number of fuel type.

- *The constraint of power balance:*

This constraint is applied to ensure the balance between the power generated by all generating sources and the amount of power required by load and loss, as shown in the following expression: .

$$\sum_{n=1}^{N_{TGU}} PTG_n + \sum_{i=1}^{N_{SP}} PSL_i + \sum_{k=1}^{N_{WT}} PWT_k = PDN + PL \tag{3}$$

Where, $\sum_{n=1}^{N_{TGU}} PTG_n$ is the total power generated by all TGUs; $\sum_{i=1}^{N_{SP}} PSL_i$ and $\sum_{k=1}^{N_{WT}} PWT_k$ are respectively, the total power supplied by all solar power plants (SPs) and all wind power plant (WTs) connected with the given system with N_{SP} and N_{WT} are, respectively, the number of SPs and WTs connected with the system ; PDN and PL are, respectively, the power demanded by all load and the amount of power loss.

The power loss in Equation (4) is determined using the following expression:

$$PL = \sum_{n=1}^{N_{TGU}} \sum_{q=1, n\neq q}^{N_{TGU}} PTG_n LC_{nq} PTG_q + \sum_{n=1}^{N_{TGU}} LC_{0n} PTG_n + LC_{00} \tag{4}$$

Where, LC_{nq}, LC_{0n}, and LC_{00} are the loss coefficients.

- *The constraints of TGU's operation*

This constraint is about the limitation of the power output generated by each TGU which must be variated within the minimum and maximum value:

$$PTG_n^{low} \le PTG_n \le PTG_n^{high} \tag{5}$$

Where, $P_{TGS,n}^{lst}$ and $P_{TGS,n}^{hst}$ are the lowest and highest amount of power produced by the TGS n; $P_{TGS,n}$ is the amount of power produced by the TGS n.

- *The constraints of SPs and WTs*

The operational constraints of SPs and WTs are modeled as the following expressions:

$$PSL_i^{low} \le PSL_i \le PSL_i^{high} \tag{6}$$

$$PWT_k^{low} \le PWT_k \le PWT_k^{high} \tag{7}$$

Where, P_{WTP}^{lst} and P_{WTP}^{hst} are the lowest and the highest value of power supplied by WPP; P_{SLP}^{lst} and P_{SLP}^{hst} are the lowest and the highest value of power supplied by SLP; P_{WTP} and P_{SLP} are the power supplied by the WPP and the SLP, respectively.

III. The Applied Method

TTAO is a novel meta-heuristic algorithm that is developed based on similar triangles. With iterative evolution, new vertexes are constantly generated in the search space and used to constitute similar triangles of different sizes. The execution of the iterative evolution is also the main foundation of the update mechanism, which is the main difference between TTAO and other meta-heuristic algorithms. The mathematical expression of the update mechanism will be briefly shown in two phases as follows:

- *Phase 1*

In the first phase, all the solutions are updated using the following expression:

$$X_t^{new} = \varepsilon \times X_{Best} + (1 - \varepsilon) \times X_t \tag{8}$$

And then

$$X_t^{new} = \begin{cases} X_t, if\ F_{X_{Best}} \le F_{X_t} \\ X_t^{new}, \quad else \end{cases} \tag{9}$$

In the Eqs. (8) – (9), X_t^{new} is the new solution t with t = 1, 2, …, *NPz* with *NPz* is the population size; ε is the random value in the interval [0,1]; X_{Best} is the best solution of the population; X_t is the current solution; $F_{X_{Best}}$ and F_{X_t} are, respectively, the fitness value of the best solution of the population and the current solution.

- *Phase 2*

The update process for new solutions in the second phase is executed as follows:

$$X_t^{new} = X_{t-Best} + \sigma \times (X_{Best} - X_{t-Best}) \tag{10}$$

With

$$\sigma = \ln\left(\frac{e - e^3}{It^{max} - 1} \times It + e^3 - \frac{e - e^3}{It^{max} - 1}\right) \quad (11)$$

In the Eqs (10) and (11), X_{t-Best} is the best so far of solution X_t; σ is the amplifying factor; It^{max} is the maximum setting of iteration; and finally, It is the current index of iteration.

IV. Results and Discussions

In this section, TTAO is applied to solve the RE-ELD with the main objective function, as shown in section 2 above, which is minimizing the OEF in the power system comprised of 10 TGUs with 2700MW of load demand. Moreover, a 100MW SP and 150MW WP are also connected to the grid, aiming to partly alleviate the adverse effects on the environment caused by TGU's operation. Besides, the multiple fuel constraint of each TGU is also taken into account while applying TTAO to solve the considered problem. The results achieved by TTAO are compared with Arctic puffin optimization (APO) [??], which is also a new meta-heuristic proposed in early 2024. For a fair comparison, both APO and TTAO are using the same presets in terms of population size (*NPz*) and the maximum number of iterations (It^{max}), which are equally set at 20 and 50. Additionally, APO and TTAO will execute 50 trial tests for their best solution before comparisons

All the coding and needed simulations are conducted on the personal computer with the basic specifications as follows: a 2.35 GHz of the central processing unit (CPU) pairing with 16 GB of random accessing memory (RAM). MATLAB programing language version 2020a is the main foundation for all the works.

Figure 1 shows the results achieved by APO and TTAO after 50 trial tests. In the figure, TTAO can reach more optimal values than APO, and besides, the fluctuation among all 50 fitness values achieved by TTAO is clearly less than APO. That means that TTAO can offer more stability while dealing with the considered problem than APO.

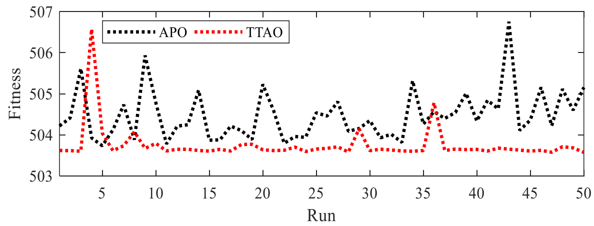

Figure 1. The results of APO and TTAO after 50 trial runs

Figures 2a, 2b and 2c display the minimum, average, and maximum convergence curves achieved by APO and TTAO. Figure 2a shows that TTAO can reach the optimal value of OFE after around 30 iterations for its best run, while APO cannot even at the last iteration. The observation in Figures 2b and 2c also indicates that TTAO is superior to APO while reaching the best value earlier than APO.

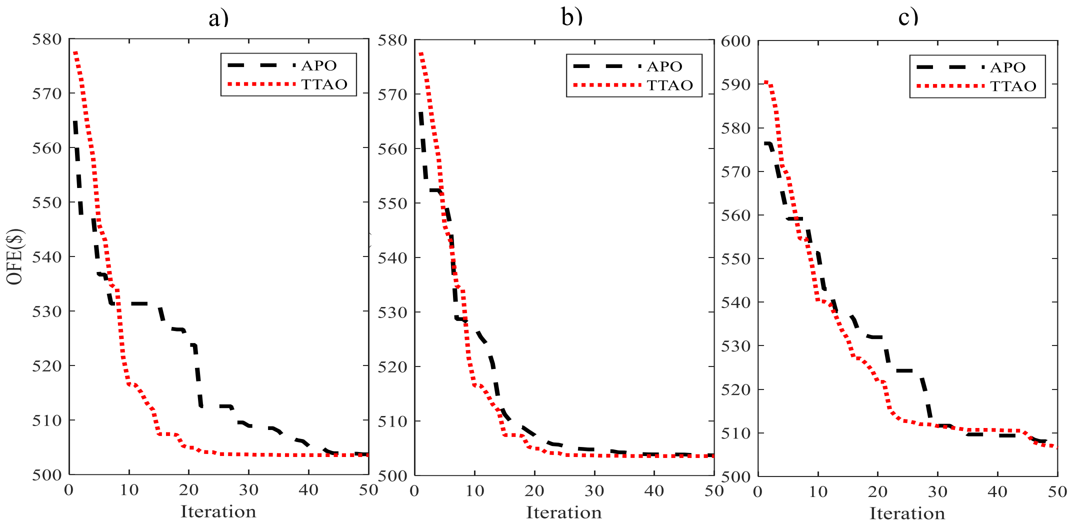

Figure 2. The minimum, average, and maximum convergences achieved by APO and TTAO for their best run

Figure 3 presents a detailed comparison between APO and TTAO on particular criteria. The two algorithms evaluate their best results on Minimum OEF (Min. OEF), Average OEF (Aver. OEF), and Maximum OEF (Max. OEF). The bar chart indicates that TTAO is more cost-effective than APO \$0.16, \$0.722, and \$0.1794 for all three criteria, respectively.

In Figure 4, the power output of each TGU found by APO and TTAO in the given system is presented for the minimum solution and the maximum solution. While investigating in detail, the advantages regarding the cost-effectiveness of TTAO are based on the optimal allocation of needed power to the TGU with cheaper OF value. This mechanism is also right for both the minimum and maximum solution.

Figures 5 and 6 show the OF value for each TGU in two cases corresponding to the minimum and maximum solution presented in Figure 4.

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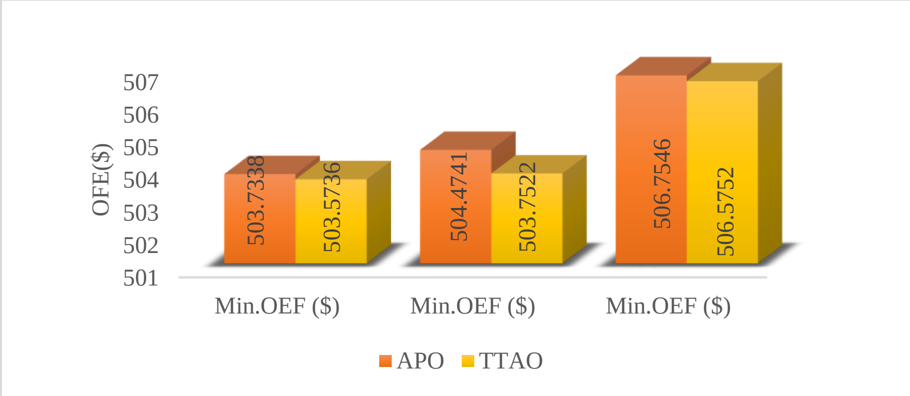

Figure 3. The results comparison of the two applied algorithms on different criteria

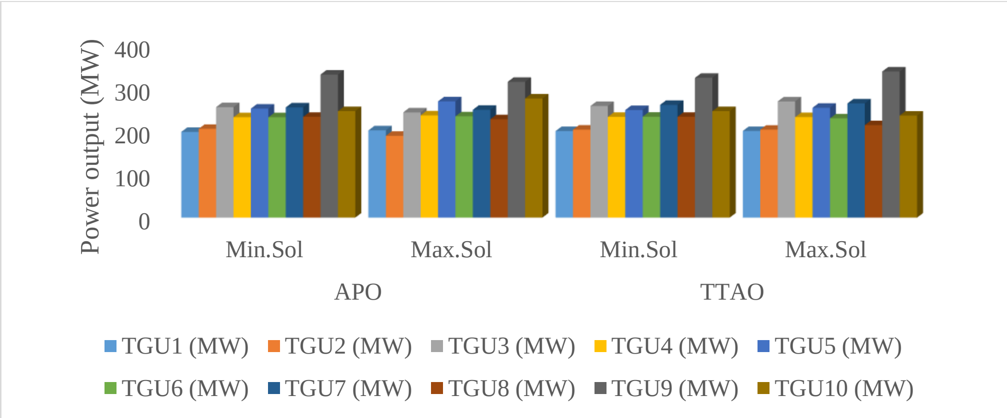

Figure 4. The generation of all the TGUs given by APO and TTAO corresponding to the minimum and maximum OEF

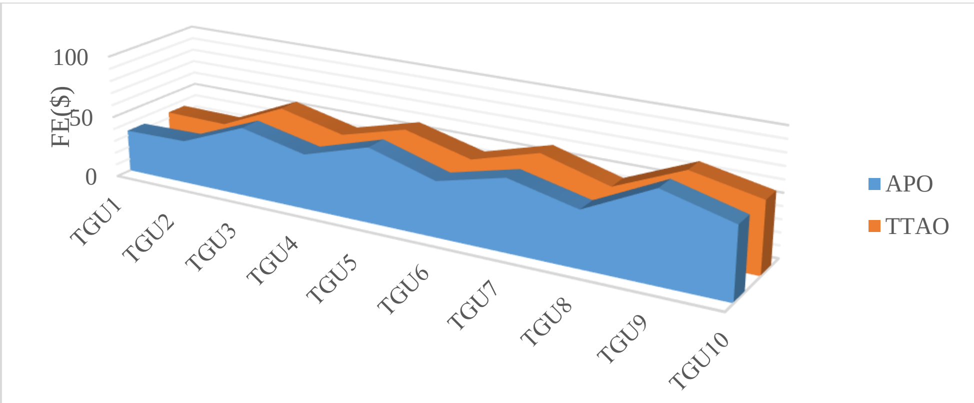

Figure 5. The fuel expenditure for each TGU in the system achieved by APO and TTAO for the case of minimum OEF

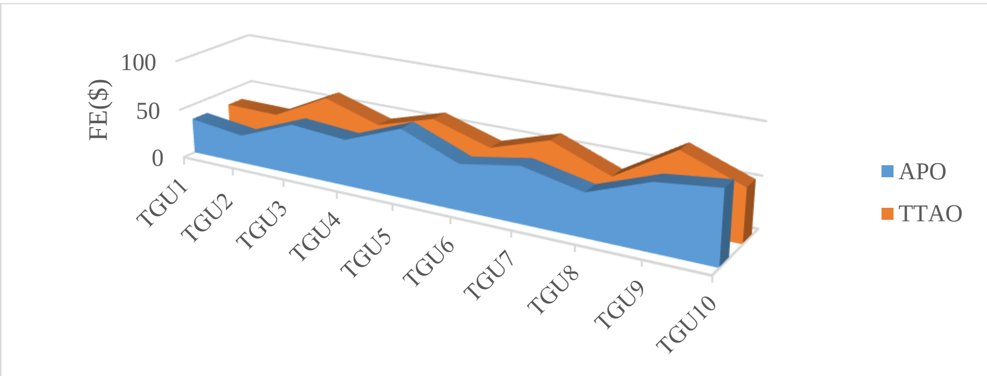

Figure 6. The fuel expenditure for each TGU in the system achieved by APO and TTAO for the case of maximum OEF

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V. CONCLUSIONS

This study successfully employs two innovative meta-heuristic algorithms, Arctic puffin optimization (APO) and Triangulation topology aggregation optimizer (TTAO), to establish the optimal allocation of all thermal generating sources. The main purpose of the whole study is to minimize the overall fuel expenditure of all thermal generating units in a power system to meet the load demand of 2700 MW. Besides, the power loss and the multiple fuel constraints of all thermal generating units are all successfully considered while solving the problem. The algorithms were compared using three criteria: minimum, average, and maximum overall fuel expenditure. Despite identical parameter settings for population size and maximum iterations, TTAO consistently outperformed APO across all criteria. Specifically, TTAO is more cost-effective than APO, which is $0.16 in Min. OEF, $0.722 in Aver. OEF, and $0.1794 in Max. OEF. Besides, TTAO also offers a higher degree of stability than APO when dealing with the problem considered. By all these results, TTAO is acknowledged to be an effective computing method, and we highly suggest using TTAO to solve such RE-ELD problem.

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