Marine Predators Algorithm and Tunicate Swarm Algorithm for Power System Economic Load Dispatch

Oluwafemi Ajayi, Reolyn Heymann and Ewaoche John Okampo
Centre for Collaborative Digital Networks
Department of Electrical and Electronic Engineering Science, University of Johannesburg,
South Africa.

Abstract

This article presents two novel methods based on the Marine Predators Algorithm (MPA) and the Tunicate Swarm Algorithm (TSA) for solving the economic dispatch problem in the electric power system. The objective of the study is to satisfy the power system's load demand and the operational constraints while incurring the minimum possible fuel cost. The objective function of the optimization is represented as the quadratic cost functions of the generators in the system. A penalty function is also incorporated into the objective function to ensure the solutions produced by MPA and TSA do not violate the system's operational constraints. The MPA and TSA models have been implemented on two test systems with six, and fifteen generator units. To determine the effectiveness of the proposed method to solve the ED problem, the results obtained using the MPA and TSA have been compared with other methods in the literature. The results show that the MPA and TSA perform very competitively with other methods.

Keywords
Economic Dispatch, Marine Predators Algorithm, Optimization and Tunicate Swarm Algorithm.

Biographies

Oluwafemi Ajayi is a PhD candidate in Electrical and Electronic Engineering at the University of Johannesburg. He received the B.Sc. (Honors) in Electrical and Electronics Engineering from Covenant University (2016) and M.Sc. degree in Electrical and Electronic Engineering from the University of Johannesburg (2019). His research interests cut across energy optimization, mathematical optimization techniques and artificial intelligence. He is a registered Candidate Engineer with the Engineering Council of South Africa. He is also registered as a Student Member with the South African Institute of Electrical Engineers.

Reolyn Heymann (PhD) is the Director of the Centre for Collaborative Digital Networks in the Faculty of Engineering and the Built Environment at the University of Johannesburg, South Africa. She is the chair of the IEEE South Africa Information Theory Society and the faculty representative of the UJ IEEE-HKN honors student chapter. She is also a senior lecturer at the University of Johannesburg where she obtained her D.Ing degree in 2016 in digital communications, specifically coding theory. She received her B.Ing Electrical and Electronic Engineering degree (cum laude) and B.Sc Information Technology degree at the Rand Afrikaans University in 2004. She received her M.Ing Electrical and Electronic Engineering degree (cum laude) from the University of Johannesburg in 2007. Her research is focused on Engineering Education, Artificial Intelligence, Serious Games applied in health and education, digital communications and networking.

Okampo John Ewoche is currently a PhD student of the department of Electrical and Electronic Engineering science, University of Johannesburg, South Africa. He holds a Bachelor of Engineering (B.Eng) degree and Master of Engineering (M.Eng) degree in Electrical and Electronic Engineering from Caritas University, Enugu and University of Port Harcourt, Nigeria respectively. His research interests include renewable energy systems, simulation, application of FACTS devices and artificial intelligence for power system optimization and reliability.

1. Introduction and Literature Review

With continuous increase in global energy demand, it has become imperative to continually investigate new ways to reduce the cost of electricity generation, which is the largest financial component in the electric power system. Economic dispatch (ED) is an optimization exercise that seeks to optimally assign generation resources to meet a load requirement in a given power system with the aim of minimizing cost while satisfying all operational equality and inequality constraints (Al Farsi et al., 2015).

Researchers have developed a variety of methods in efforts to solve the ED optimization problem. These methods cut across deterministic and nondeterministic categories and some of them include Lagrange Multiplier, linear and quadratic programming (Kumar & Alwarsamy, 2015). Nevertheless, as a result of the complexities of power system optimization tasks, substitute methods are investigated. Metaheuristic algorithms have gained popularity in solving optimization problems due to their *black box* approach to solving optimization problems (Hussain et al., 2019). Metaheuristic methods including but not limited to Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Exchange Market Algorithm (EMA), Gravitational Search Algorithm (GSA), Tabu Search (TS), Ant Colony Optimization (ACO), and Ant Lion Optimizer (ALO) have been developed and used to solve ED optimization problems in the literature. These methods have produced some promising results in solving the ED problem and other optimization problems. Modified versions of some of these methods have also been used in the literature. In (Azkiya et al., 2018), GA was used to solve the ED problem for a 500KV thermal power system. The GA was used to analyze the power system's heat rate data and cost functions of the generator units in the system to obtain the minimum fuel cost associated with system's electricity generation. For simplicity sake, the transmission losses were neglected in their study. In (Ouiddir et al., 2005), GA was also used to solve the ED problem considering the Western Algerian power system. The transmission losses were accounted for in their study through the application of Newton-Raphson method. Based on comparison with deterministic methods, the GA outperformed the deterministic methods in terms of finding the minimal fuel cost for electricity generation to satisfy the system's load demand. The work presented in (Aliyari et al., 2014) examined the use of a GA variant called Non-dominant Sorting Genetic Algorithm (NSGA) to solve the ED problem while also considering emissions dispatch to form a multi-objective optimization problem. To determine the effectiveness of the NSGA method in solving the multi-objective constrained optimization problem, the model was implemented on the IEEE 30-bus system. Results from the study show that the multi-objective NSGA obtained the best fuel and emission costs for the test system in comparison with methods like PSO and Differential Evolution (DE). The authors of (Tofighi et al., 2011) present the application of an improved GA method to solve the ED problem while considering valve point effects. It was observed that the inclusion of valve point effects in the model introduced a greater degree of nonlinearity and local optima to the search space. Based on results obtained from implementing the method on two test systems, it was found that the improved GA performed competitively in relation to other methods. In (Purlu & Turkay, 2018), a comparative study on the application of GA and PSO to solve a dynamic economic dispatch with valve point effect is presented. Based on results obtained from implementing the models on two test systems with three and ten generator units, it was found that the GA and PSO outperformed other methods they were compared with. PSO also found better fuel costs than the GA for both test systems. A PSO variant called Species-based Quantum-PSO (SQPSO) was proposed to solve the ED problem in (Hosseinnezhad et al., 2014). Their study found that the SQPSO demonstrated high exploitation prowess and superiority in finding optimal solutions in comparison to conventional methods. In (Xin-gang et al., 2020), the authors proposed an optimized Quantum-PSO (QPSO) to solve an Environmental ED problem. The optimization was done to leverage the fast convergence ability of the DE and the diversity of solutions of the GA for the PSO. Results show that the optimized QPSO performed better than the conventional QPSO for both single and multi-objective optimization problems. A hybrid DE and GSA method for solving nonconvex ED was proposed in (Le et al., 2015), and it produced promising results. In (Basu, 2014), the scaling factor used in DE to search the solutions space was replaced by a Gaussian random variable. The improved DE showed higher efficiency in searching the solution space for optimal solutions to the ED problem being considered. In (Pattanaik et al., 2019), a comparison of the application GA, DE, PSO, Evolutionary Programming (EP) and Simulated Annealing (SA) to solve a dynamic ED problem is presented. The five methods considered were implemented on a system made up of ten generator units. The results presented in the article showed that DE performed best in finding the least cost and had the least execution time. The robustness and fast convergence abilities of the GSA was highlighted in (Swain et al., 2012), where the authors applied the method to solve the ED problem considering two test systems with three and thirteen generator units. To avoid local optimal solutions, the GA mutation process was integrated to the GSA to produce a model for solving the ED problem in (Huang et al., 2016). The improved method performed competitively in terms of finding the optimal fuel cost and stability of the algorithm in comparison with other metaheuristic algorithms. A TS method was proposed for solving the ED problem with line flows considerations in (Naama et al., 2013). The model which was implemented on IEEE 57 bus test system outperformed methods like GA and Quasi Newton in finding the minimum fuel cost. The TS model also produced significant gains in execution time. In (Ghorbani, 2016), the author proposed an Exchange Market Algorithm (EMA) method to solve a combined heat and power ED problem. The work presented in (Alazemi & Hatata, 2019) considers the integration of demand response in solving the ED problem using ALO. The ED problem was formulated as a cost and emissions minimization task, implemented on IEEE standard six and thirty bus test systems. The ALO outperformed other methods it was compared with in that study. In (Ajayi et al., 2018), the authors present a comparative study of the performance of EMA and ALO in solving the ED problem. Based on results obtained from two test systems, the authors highlighted a trade-off in the performance of the two methods in finding the system's optimal solution.

1.1 Objectives

Since the No Free Lunch theorem says that no metaheuristic optimization algorithm is capable of solving every optimization problem, then it is important to investigate new methods to solve optimization problems (Adam et al., 2019). On this basis, this paper presents two novel methods to solve the ED optimization problem while giving considerations to valve point effects. The first method presented is the Marine Predators Algorithm (MPA) and the second is Tunicate Swarm Algorithm (TSA). The MPA is a population-based metaheuristic search algorithm that is inspired by the interactions between predators and preys in water (Faramarzi et al., 2020). MPA employs characteristics of both Levy flight and Brownian motion strategies to navigate the search space to find optimal solutions. The TSA is a swarm intelligence algorithm based on the jet propulsion-like movement and swarm attributes of tunicates in their navigation and search for food (Kaur et al., 2020). To validate the efficacy of MPA and TSA to solve the ED optimization problem, the two methods have been implemented on four test systems with six, thirteen, fifteen and forty generators. The simulation of the models has been done in MATLAB. To have a sense of the relative performance of the proposed methods to solve the ED problem, their results have been compared with other methods like Genetic Algorithm (GA), Tabu Search (TS), Chaotic Bat Algorithm (CBA), Salp Swarm Algorithm (SSA), etc. It is observed that both the MPA and TSA methods performed very competitively in solving the ED problem.

The rest of the paper is structured as follows. Section 2 presents the ED formulation, section 3 presents an overview of MPA, section 4 presents an overview of TSA, results from the models are presented and discussed in section 5, and the conclusion to the study is given in section 6.

2. Economic Dispatch Formulation

In solving the ED problem, the main objective is to determine the amount of output power from each generator in the system that will result in the minimum possible fuel cost in electricity generation while obeying a set of constraints(Azkiya et al., 2018; Ciornei & Kyriakides, 2013). The set of constraints considered in this study are a combination of equality and inequality constraints. The objectives and formulations are therefore represented as follows.

2.1 Objective Function

The overall cost function of the ED problem is represented using the following quadratic function (Rezaie et al., 2019).

$$FC = \sum_{k=1}^{nG} [a_k + b_k P_{Gk} + c_k P_{Gk}^2], \qquad for\ k = \{1,2,3, \dots nG\} \tag{1}$$

where FC represents the overall fuel cost in \$/h for all generators in the system, a_k, b_k and c_k represent the cost coefficient of the kth generator, P_{Gk} is the power output of generator k, and nG represents the number of generators in the system.

For practicability, the cost function for electric power systems in which the valve point effect is considered is represented as follows (Güvenç et al., 2012; Rezaie et al., 2019).

$$F(P_{Gk}) = \sum_{k=1}^{nG} \left[a_k + b_k P_{Gk} + c_k P_{Gk}^2 + \left|d_k sin\left\{e_k\left(P_{Gk}^{min} - P_{Gk}\right)\right\}\right|\right], \qquad for\ k = \{1,2,3, \dots nG\} \tag{2}$$

Where d_k and e_k are the cost coefficients for generator units that reflect the valve point effect. These d_k and e_k coefficients are only used in cases where the valve point effect is considered.

2.2 Power Balance Constraint

This is an equality constraint that ensures the total output from all generators in the system satisfies the system load as well as losses. The power balance constraint is expressed as follows (Güvenç et al., 2012).

$$\sum_{k=1}^{nG} P_{Gk} = P_d + P_l \tag{3}$$

Where P_d is the load demand in the system and P_l represents the power losses in the system. In this study, the power losses in the system have not been taken into account because the study is more focused on finding the amount of power generated by the system to meet the load demand. All generators and load demand are assumed to be connected to a single bus bar (Lin & Magnago, 2017).

2.3 Generator Output Limit Constraint

This inequality constraint ensures that every generator in the power system operates within the manufacturer's power output limits. It is expressed as follows (Güvenç et al., 2012).

$$P_{Gk(\min)} \leq P_{Gk} \leq P_{Gk(\max)} \tag{4}$$

Where $P_{Gk(\min)}$ and $P_{Gk(\max)}$ represent the lower and upper limits of the kth generator's power output.

3. Marine Predators Algorithm

This is a population-based metaheuristic algorithm that is modeled after the interaction between aquatic predators and preys. The algorithm attempts to find the global optima to a given optimization by mimicking the foraging strategies of marine predators. The MPA randomly initializes a solution set that is uniformly distributed across the search space. This is achieved through the following expression (Faramarzi et al., 2020).

$$G_0 = G_{min} + rand(G_{max} - G_{min}) \tag{5}$$

Where G_{min} and G_{max} represent the lower and upper limits of the variable, $rand$ represents a uniform vector whose values are within the range [0, 1].

The MPA then uses the fitness function to evaluate the suitability of each initialized solution in the set. Based on their fitness, a matrix of Elites (candidate solutions with the best fitness values) is created. The members of the Elite group represent the top predators in the population and the Elite matrix is represented as follows (Faramarzi et al., 2020).

$$Elite = \begin{bmatrix} G_{1,1}^I & G_{1,2}^I & \cdots & G_{1,d}^I \\ G_{2,1}^I & G_{2,2}^I & \dots & G_{2,d}^I \\ \vdots & \vdots & \vdots & \vdots \\ G_{n,1}^I & G_{n,2}^I & \cdots & G_{n,d}^I \end{bmatrix} \tag{6}$$

Where G^I represents the vector of the top predator that is duplicated n times to create the Elite matrix.
The predators search for prey using another matrix called Prey which contains information about the position of the prey. The Prey matrix whose dimension is same as the Elite matrix is represented as follows (Faramarzi et al., 2020).

$$Elite = \begin{bmatrix} G_{1,1} & G_{1,2} & \cdots & G_{1,d} \\ G_{2,1} & G_{2,2} & \dots & G_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ G_{n,1} & G_{n,2} & \cdots & G_{n,d} \end{bmatrix} \tag{7}$$

Where $G_{i,j}$ represents the ith prey's jth dimension.

MPA sections the optimization process into three scenarios based on the velocity ratio of predator to prey. The velocity ratio is high in the first scenario, the velocity ratio is approximately unity in the second scenario and the velocity ratio is low in the third scenario. Each scenario is executed for a third of the total number of epochs.

The first scenario where the velocity ratio is high is modeled as follows (Faramarzi et al., 2020).

While *Cur_Epoch* < 1/3 *Max_Epoch*

$$\overrightarrow{stepsize_i} = \overrightarrow{D_b} \otimes \left(\overrightarrow{Elite_i} - \overrightarrow{D_b} \otimes \overrightarrow{Prey_i}\right), \qquad for\ i = 1, \dots, n$$

$$\overrightarrow{Prey_i} = \overrightarrow{Prey_i} + Q * \vec{D} \otimes \overrightarrow{stepsize_i} \tag{8}$$

Where D_b is a vector representing the Brownian motion, Q has a value of 0.5, D is a vector whose values are within the range [0, 1]. *Cur_Epoch* represents the current iteration and *Max_Epoch* represents the total number of epochs. The step size in this scenario is high and allows for high exploration.

In the second scenario of unit velocity ration, the prey moves using Levy flight strategy while the predator uses Brownian motion. The first half of the population set represents the prey while the second half represent the predators. These two groups are modeled as follows (Faramarzi et al., 2020).

First half of solutions:

While 1/3 *Max_Epoch* < *Cur_Epoch* < 2/3 *Max_Epoch*

$$\overrightarrow{stepsize_i} = \overrightarrow{D_L} \otimes \left(\overrightarrow{Elite_i} - \overrightarrow{D_L} \otimes \overrightarrow{Prey_i}\right), \qquad for\ i = 1, \dots, \frac{n}{2}$$

$$\overrightarrow{Prey_i} = \overrightarrow{Prey_i} + Q * \vec{D} \otimes \overrightarrow{stepsize_i} \tag{9}$$

Where $\overrightarrow{D_L}$ represents the movement of prey based on Levy flights. The small step sizes associated with this group make them suitable for exploitation activities.

Second half of solutions:

$$\overrightarrow{stepsize_i} = \overrightarrow{D_b} \otimes \left(\overrightarrow{Elite_i} - \overrightarrow{D_b} \otimes \overrightarrow{Prey_i}\right), \qquad for\ i = \frac{n}{2}, \dots, n$$

$$\overrightarrow{Prey_i} = \overrightarrow{Elite_i} + Q * CF \otimes \overrightarrow{stepsize_i} \tag{10}$$

Where $CF = \left(1 - \frac{Cur\_Epoch}{Max\_Epoch}\right)^{\frac{2*Cur\_Epoch}{Max\_Epoch}}$ is a parameter used to control the step sizes of the second half of the population based on Brownian motion.

In the third scenario where the velocity ratio is low and associated with high exploitation, the predators switch movement strategy. Here the predator uses the Levy flight method and this scenario is represented as follows (Faramarzi et al., 2020).

While *Cur_Epoch* > 2/3 *Max_Epoch*

$$\overrightarrow{stepsize_i} = \overrightarrow{D_L} \otimes \left(\overrightarrow{D_L} \otimes \overrightarrow{Elite_i} - \overrightarrow{Prey_i}\right), \qquad for\ i = 1, \dots, n$$

$$\overrightarrow{Prey_i} = \overrightarrow{Elite_i} + Q * CF \otimes \overrightarrow{stepsize_i} \tag{11}$$

To combat the challenge of local optima trapping, a condition based on Fish Aggregating Devices (FADs) effect is used. This helps the MPA to make longer jumps in the search space and escape the local optima. This FADs effect is represented as follows.

$$\overrightarrow{Prey_i} = \begin{cases} \overrightarrow{Prey_i} + CF\left[\overrightarrow{G_{min}} + \vec{D} \otimes \left(\overrightarrow{G_{max}} - \overrightarrow{G_{min}}\right)\right] \otimes \vec{T}, & if\ r \leq FADs \\ \overrightarrow{Prey_i} + [FADs(1-r) + r]\left(\overrightarrow{Prey_{r1}} - \overrightarrow{Prey_{r2}}\right), & if\ r > FADs \end{cases} \quad (12)$$

Where $FADs$ = 0.2, T is a vector containing binary numbers, $r1$ and $r2$ are the indexes of the Prey matrix.

3.1 Implementation of MPA to Solve ED Problem

In this section, a new metaheuristic optimization algorithm based on the foraging activities of marine predators for solving the ED problem is defined as follows.

Step 1. Identification of search space.
Let $P_{Gk} = (P_{G1}, P_{G2}, \dots, P_{GnG})$
Where P_{Gk} represents the position of the kth generator in the search space which is the real power produced by the kth generator unit.

Step 2. Initializing the population of generators.
This is achieved by specifying P_{Gk} as a random variable whose values represent the real power output of the kth generator unit. The P_{Gk} values must be within a range $\left[P_{Gk(min)}, P_{Gk(max)}\right]$.

Step 3. Compute the fuel cost for each generator unit.
A penalty function is introduced to account for the power balance constraint. Here, the absolute value equivalent to the degree of violation of the power balance constraint is added to the cost function. This was done to ensure candidate solutions that violate the equality constraints are disadvantaged in the population based on their degree of violation of said constraint. The cost function then becomes:

$$F(P_{Gk}) = \sum_{k=1}^{nG} \left[a_k + b_k P_{Gk} + c_k P_{Gk}^2 + \left|d_k sin\left\{e_k\left(P_{Gk}^{min} - P_{Gk}\right)\right\}\right|\right] + (m * h_k) \quad (13)$$

Where m is a constant whose value is determined through trial and error, and h_k is the magnitude of difference between the total power generation and the load demand in the system.

Step 4. Update the Elite matrix, Prey matrix for $k = 1,2, \dots, nG$.

Step 5. Based on the velocity ratio, calculate the step size of the solutions.

Step 6. Redo steps 4 - 6 till stopping criterion is satisfied.

Step 7. End and return the optimal ED solution.

4. Tunicate Swarm Algorithm

This is another metaheuristic algorithm that is based on swarm intelligence. The algorithm is modeled after two behaviors that inform the foraging activities of tunicates. These two behaviors are jet propulsion-like movement and swarm intelligence of the tunicates (Kaur et al., 2020). In modeling the jet propulsion-like motion, the tunicate must satisfy the following conditions which are avoidance of conflicts between tunicates, maintain movement in the direction of the best tunicate, and remain in close proximity to the best tunicate.

To avoid conflicts with other tunicates, the position of new tunicates (search agents) is determined using vector $\vec{B}$ through the following (Kaur et al., 2020).

$$\vec{B} = \frac{\vec{E}}{\vec{P}} \tag{14}$$

$$\vec{E} = s_2 + s_3 - \vec{R} \tag{15}$$

$$\vec{R} = 2 * s_1 \tag{16}$$

$$\vec{P} = \lfloor U_{min} + s_1 * U_{max} - U_{min} \rfloor \tag{17}$$

Where $\vec{E}$ is the gravitational force, $\vec{P}$ represents the social forces between tunicates, $\vec{R}$ is the water flow advection, s_1, s_2 and s_3 are random values whose values are within the range [0, 1], U_{min} and U_{max} are the initial and lesser speeds to initiate social interaction.

To maintain movement towards the best tunicate, the following is used (Kaur et al., 2020).

$$\overrightarrow{DT} = \left|\overrightarrow{FT} - r_{and} * \overrightarrow{U_u(x)}\right| \tag{18}$$

Where $\overrightarrow{DT}$ is the distance between the tunicate and food source (which is the global optima), $\overrightarrow{FT}$ is the position of the global optima, $\overrightarrow{U_u(x)}$ is the tunicate's position, and r_{and} is a random number within the range of [0, 1].

To satisfy the third condition, which relates to convergence towards the global optima, the search agents make sure they remain close to the best tunicate through the following (Kaur et al., 2020).

$$\overrightarrow{U_u(x')} = \begin{cases} \overrightarrow{FT} + \vec{B} * \overrightarrow{DT}, & if\ r_{and} \geq 0.5 \\ \overrightarrow{FT} - \vec{B} * \overrightarrow{DT}, & if\ r_{and} \leq 0.5 \end{cases} \tag{19}$$

Where $\overrightarrow{U_u(x')}$ contains the updated position of tunicates considering the position of the global optima.

To model the swarm behavior of tunicates, TSA saves the first two best solutions to the optimization problem and updates the positions of other tunicates based on these. This operation is expressed as follows (Kaur et al., 2020).

$$\overrightarrow{U_u(x+1)} = \frac{\overrightarrow{U_u(x)} + \overrightarrow{U_u(x+1)}}{2 + s_1} \tag{20}$$

4.1 Implementation of TSA to Solve ED Problem

In this section, the application of the tunicates-inspired optimization algorithm to solve the ED problem is presented.

Step 1. Identification of search space.
Let $P_{Gk} = (P_{G1}, P_{G2}, \dots, P_{GnG})$
Where P_{Gk} represents the position of the kth generator in the search space which is the real power produced by the kth generator unit.

Step 2. Initialize the population of generators.
P_{Gk} was specified as a random variable whose values represent the real power output of the kth generator unit. The P_{Gk} values must be within a range $\left[P_{Gk(min)}, P_{Gk(max)}\right]$.

Step 3. Compute the fuel cost for each generator unit.
A penalty function is introduced to account for the power balance constraint. The penalty function ensures candidate solutions that violate the equality constraints are disadvantaged in the population based on their degree of violation of said constraint.

Step 4. Explore the best combination of the generator outputs in the search space.

Step 5. Update the position (real power output) of each generator unit.

Step 6. Ensure equality and inequality constraints are satisfied.

Step 7. Compute fitness values of updated generator positions.
Update the positions of the generators if a better solution has been found.

Step 8. Redo steps 5 - 8 till stopping criterion is satisfied.

Step 9. End and return the optimal ED solution.

5. Results and Discussion

The MPA and TSA models have been implemented in MATLAB R2018b version, on an 8GB RAM, with 2.6GHz Intel Core i5 processor. To assess the effectiveness of the MPA and TSA methods in solving the ED problem, both methods have been implemented on two test systems with six and fifteen generators based on the data obtained from (Salem et al., 2019). The two test systems considered have been widely used in other studies that have investigated the ED optimization problem. The stopping criterion for both the MPA and TSA methods is the maximum number of epochs which was set to 500. The model simulations were done twenty times for both MPA and TSA on all test systems. The results obtained using MPA and TSA have also been compared with other methods like Simulated Annealing (SA), Tabu Search (TS), Salp Swarm Algorithm (SSA), Chaotic Bat Algorithm (CBA), Particle Swarm Optimization (PSO), Multiple Tabu Search (MTS) and Backtracking Search Algorithm (BSA).

5.1 Test System 1: 6 Generators

The six generators in this system are modeled to represent their quadratic cost functions. The overall load demand in the system is 1263MW (Salem et al., 2019). In this case, the valve point effect is not taken into account. The proposed MPA and TSA ED models have been simulated ten times for this test system and the findings are presented in this section. The input data for the model is presented in Table 5 of the appendix.

5.1.1 Numerical Results

Table 1. Results comparison for test system 1

Method	Best Fuel Cost ($/h)	Mean Fuel Cost ($/h)	Max. Fuel Cost ($/h)	Mean Run Time (s)	S.D
SSA (Salem et al., 2019)	15444.88	15470.32	15515.83	18..82	17.95
SA (Pothiya et al., 2008)	15461.10	15488.98	15461.10	50.36	28.37
TS (Pothiya et al., 2008)	15454.89	15472.56	15454.89	20.55	13.72
CBA (Adarsh et al., 2016)	15454.76	15454.76	15450.23	0.70	2.97
MPA	15287.41	15287.41	15287.41	0.43	3.43434E-06
TSA	15296.60	15312.63	15349.15	0.38	13.87

Table 2. Proposed MPA and TSA solutions of ED for test system 1

Gen. Unit	MPA (MW)	TSA (MW)
1	450.29	445.19
2	173.90	176.28
3	266.90	265.71
4	128.01	108.72
5	175.26	200.00
6	68.64	67.10
Fuel cost ($/h)	15287.41	15296.60

Table 1 presents a comparison of the results obtained with other existing methods in the literature. For test system 1 with six generators and a load demand of 1263MW, it is observed that the proposed MPA and proposed TSA significantly outperformed methods like SSA, TS, SA and CBA in solving the ED problem as shown in Table 1. Considering the standard deviation of the MPA and TSA in Table 1, it is noticed that the MPA had a much lower standard deviation which implies it is a more stable algorithm compared to the proposed TSA in the context of this test system. Table 2 presents the optimal operational levels of each generator unit in the system as well as the best fuel costs obtained by both MPA and TSA. From Table 2 it can be seen that the six generator units in the system are scheduled to operate within their respective safe operating limits and the power balance constraint is adequately satisfied by both the MPA and TSA.

5.1.2 Graphical Results

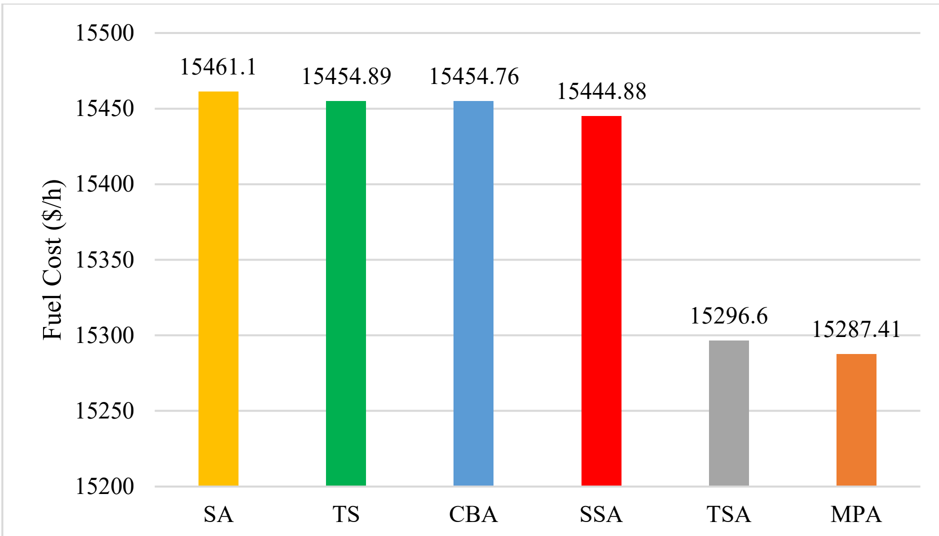

Figure 1. Comparison of best fuel costs obtained from ten simulations for test system 1

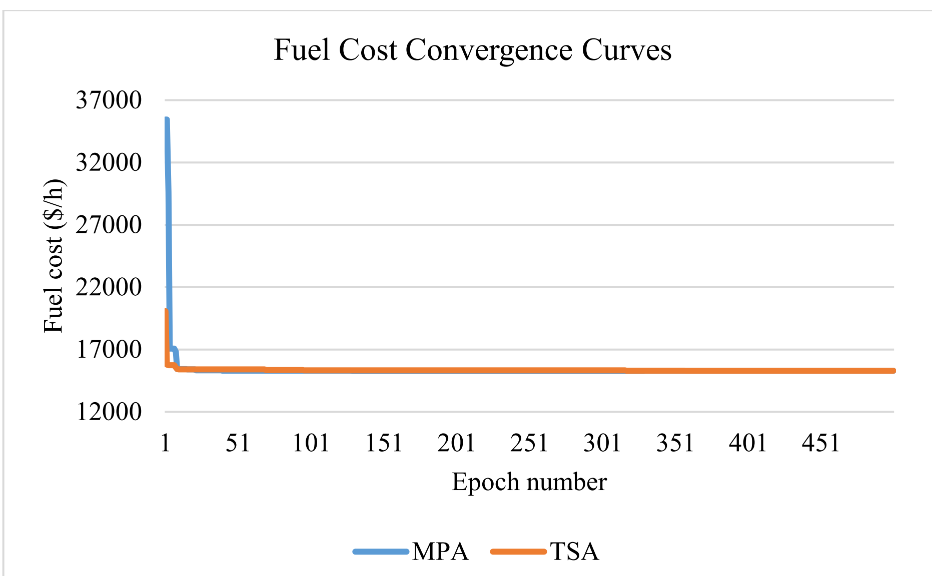

Figure 2. MPA and TSA fuel cost convergence curves for test system 1

Figure 1 shows a comparison of the best fuel costs obtained using the proposed MPA and TSA in relation to other methods. For MPA, the fuel cost is 15287.41 ($/h) and the fuel cost in TSA is 15296.60 ($/h). Figure 2 presents the fuel cost convergence curves of the proposed MPA and TSA methods. Their convergence characteristics show that the two proposed methods converge quickly and then slowly tries to improve the solutions as the epochs go on. Of the two proposed models, the MPA found a better fuel cost for this test system.

5.2 Test System 2: 15 Generators

Here, the fifteen generators in the system are expected to satisfy a total load demand of 2630MW (Salem et al., 2019). The valve point effect has also not been taken into account for this system. The proposed MPA and TSA ED models have been simulated ten times for this test system and the findings are presented in this section. Table 3 presents the results obtained using the proposed methods in relation to other existing methods. Optimal operational levels for the generator units in the system as determined by MPA and TSA are presented in Table 4. The data used to simulate the model is contained in Table 6 of the appendix.

5.2.1 Numerical Results

Table 3. Results comparison for test system 2

Method	Best Fuel Cost ($/h)	Mean Fuel Cost ($/h)	Max. Fuel Cost ($/h)	Run Time (s)	S.D
SSA (Salem et al., 2019)	32917.44	33136.03	33350.56	N/A	97.48
MTS (Pothiya et al., 2008)	32716.87	32767.21	32796.15	N/A	17.51
GA (Gaing, 2003)	33113	33228	33337	N/A	N/A
PSO (Gaing, 2003)	32858	33039	33331	N/A	N/A
BSA (Modiri-Delshad et al., 2016)	32704.45	32704.47	32704.5	N/A	0.028
MPA	32023.55	32084.94	32182.55	0.48	46.73
TSA	32133.12	32400.25	32637.16	0.3	136.16

Table 4. Proposed MPA and TSA solutions of ED for test system 2

Gen. Unit	MPA (MW)	TSA (MW)
1	420.40	297.22
2	423.98	365.31
3	129.41	121.09
4	125.56	41.11
5	341.80	470.00
6	432.10	460.00
7	453.12	465.00
8	65.34	69.90
9	57.92	67.20
10	25.10	61.79
11	77.94	24.03
12	21.05	78.59
13	25.64	38.83
14	15.63	41.99
15	15.00	28.01
Fuel cost ($/h)	32023.55	32133.12

For test system 2 consisting of fifteen generator units servicing a total load demand of 2630MW, the MPA outperformed all other methods it was compared with in finding the optimal fuel cost as shown in Table 3. The TSA also had a shorter execution time than the MPA although the MPA proved to be more stable for this test system as shown in Table 3. The electricity production levels of each generator in the system is presented in Table 4. It can be seen that the fifteen generator units in the system are also scheduled to operate within their respective safe operating limits and the power balance constraint is adequately satisfied by both the MPA and TSA.

5.2.2 Graphical Results

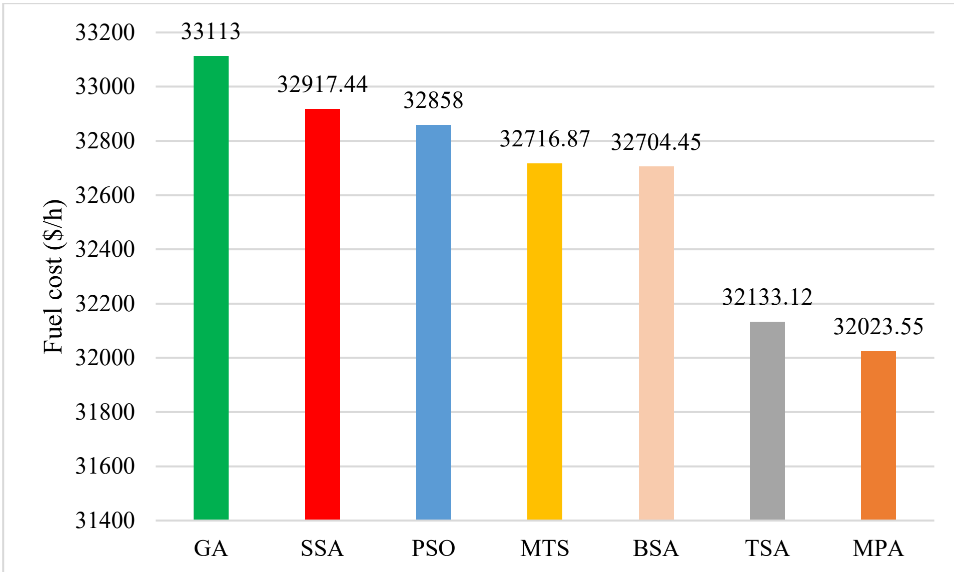

Figure 3. Comparison of best fuel costs obtained from ten simulations for test system 2

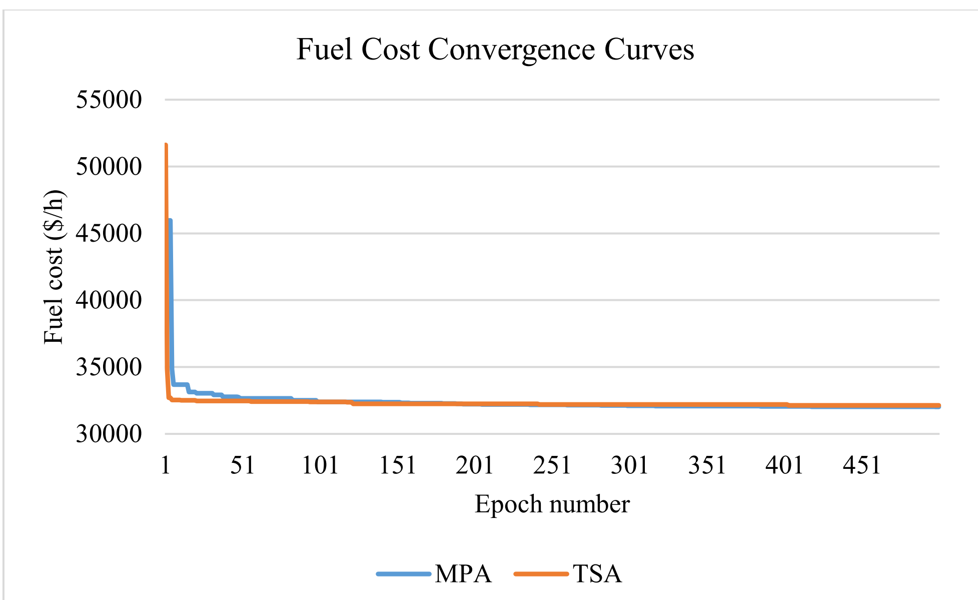

Figure 4. MPA and TSA fuel cost convergence curves for test system 2

Figure 3 shows the best fuel cost comparison found for test system 2 using MPA and TSA in relation to other existing methods. The best fuel cost found by MPA is 32023.55 ($/h). TSA came in second place with a fuel cost of 32133.12 ($/h), displacing methods like GA, PSO, MTS, BSA and SSA. Figure 4 shows the convergence curves for the proposed MPA and TSA methods for test system 2.

6. Conclusion

MPA and TSA are one of the most recent nature-inspired metaheuristic algorithms. The two algorithms have been used to solve the ED problem in this study. The models have been implemented on two test systems with unique characteristics. The first and second test systems have six and fifteen generator units respectively. The results obtained demonstrate the effectiveness and robustness of MPA and TSA to competitively solve the ED problem in comparison with other methods in the literature. The convergence curves of the proposed methods also highlight their fast convergence capabilities when applied to the two test systems. Furthermore, the promising results obtained in this study is an indication of the potential of using the MPA and TSA to solve even more complex optimization problems.

References

Adam, S. P., Alexandropoulos, S. N., Pardalos, P. M., & Vrahatis, M. N. (2019). No Free Lunch Theorem: A Review. In *Springer Optimization and Its Applications 145* (pp. 57–82). https://doi.org/10.1007/978-3-030-12767-1_5

Adarsh, B. R., Raghunathan, T., Jayabarathi, T., & Yang, X. (2016). Economic dispatch using chaotic bat algorithm. *Energy*, *96*, 666–675. https://doi.org/10.1016/j.energy.2015.12.096

Ajayi, O., Nwulu, N., & Damisa, U. (2018). A Comparison of Exchange Market Algorithm and Ant Lion Optimizer for Optimal Economic Dispatch. *2018 International Conference on Computational Techniques, Electronics and Mechanical Systems (CTEMS)*, *4*, 100–103. https://doi.org/10.1109/CTEMS.2018.8769253

Al Farsi, F. N., Albadi, M. H., Hosseinzadeh, N., & Al Badi, A. H. (2015). Economic Dispatch in power systems. *2015 IEEE 8th GCC Conference & Exhibition*, *December 2016*, 1–6. https://doi.org/10.1109/IEEEGCC.2015.7060068

Alazemi, F. Z., & Hatata, A. Y. (2019). Ant Lion Optimizer for Optimum Economic Dispatch Considering Demand Response as a Visual Power Plant. *Electric Power Components and Systems*, *47*(6–7), 629–643. https://doi.org/10.1080/15325008.2019.1602799

Aliyari, H., Effatnejad, R., & Savaghebi, M. (2014). Economic Dispatch With Genetic Algorithm. *ICTPE Conference*, *September*, 82–87.

Azkiya, N. M., Abdullah, A. G., & Hasbullah, H. (2018). Economic dispatch and operating cost optimization for thermal power in 500 KV system using genetic algorithm (GA). *IOP Conference Series: Materials Science and Engineering*, *434*(1). https://doi.org/10.1088/1757-899X/434/1/012013

Basu, M. (2014). Improved differential evolution for economic dispatch. *International Journal of Electrical Power and Energy Systems*, *63*, 855–861. https://doi.org/10.1016/j.ijepes.2014.07.003

Ciornei, I., & Kyriakides, E. (2013). Recent methodologies and approaches for the economic dispatch of generation in power systems. *International Transactions on Electrical Energy Systems*, *23*(7), 1002–1027. https://doi.org/10.1002/etep.1635

Faramarzi, A., Heidarinejad, M., Mirjalili, S., & Gandomi, A. H. (2020). Marine Predators Algorithm : A nature-inspired metaheuristic. *Expert Systems With Applications*, *152*, 113377. https://doi.org/10.1016/j.eswa.2020.113377

Gaing, Z.-L. (2003). Particle swarm optimization to solving the economic dispatch considering the generator constraints. *IEEE Transactions on Power Systems*, *18*(3), 1187–1195. https://doi.org/10.1109/TPWRS.2003.814889

Ghorbani, N. (2016). Combined heat and power economic dispatch using exchange market algorithm. *International Journal of Electrical Power and Energy Systems*, *82*, 58–66. https://doi.org/10.1016/j.ijepes.2016.03.004

Güvenç, U., Sönmez, Y., Duman, S., & Yörükeren, N. (2012). Sharif University of Technology Combined economic and emission dispatch solution using gravitational search algorithm. *Scientia Iranica*, *19*(6), 1754–1762. https://doi.org/10.1016/j.scient.2012.02.030

Hosseinnezhad, V., Rafiee, M., Ahmadian, M., & Ameli, M. T. (2014). Electrical Power and Energy Systems Species-based Quantum Particle Swarm Optimization for economic load dispatch. *International Journal of Electrical Power and Energy Systems*, *63*, 311–322. https://doi.org/10.1016/j.ijepes.2014.05.066

Huang, Y., Wang, J., & Guo, F. (2016). Economic load dispatch using improved gravitational search algorithm. *2nd ISPRS International Conference on Computer Vision in Remote Sensing (CVRS 2015)*, *9901*(Cvrs 2015), 990114. https://doi.org/10.1117/12.2234725

Hussain, K., Mohd Salleh, M. N., Cheng, S., & Shi, Y. (2019). Metaheuristic research: a comprehensive survey. *Artificial Intelligence Review*, *52*(4), 2191–2233. https://doi.org/10.1007/s10462-017-9605-z

Kaur, S., Awasthi, L. K., Sangal, A. L., & Dhiman, G. (2020). Engineering Applications of Artificial Intelligence Tunicate Swarm Algorithm : A new bio-inspired based metaheuristic paradigm for global optimization ☆. *Engineering Applications of Artificial Intelligence*, *90*(November 2019), 103541.

https://doi.org/10.1016/j.engappai.2020.103541
Kumar, C., & Alwarsamy, T. (2015). *Dynamic Economic Dispatch – A Review of Solution Methodologies*. *64 No.4*(November 2011), 517–537.
Le, L. D., Ho, L. D., Vo, D. N., & Vasant, P. (2015). Hybrid Differential Evolution and Gravitational Search Algorithm for Nonconvex Economic Dispatch. In *Proceedings in Adaptation, Learning and Optimization 2* (Vol. 2, pp. 89–103). https://doi.org/10.1007/978-3-319-13356-0_8
Lin, J., & Magnago, F. H. (2017). Power System Economic Dispatch. In *Electricity Markets: Theories and Applications* (pp. 119–146). John Wiley & Sons, Inc. https://doi.org/10.1002/9781119179382.ch5
Modiri-Delshad, M., Aghay Kaboli, S. H., Taslimi-Renani, E., & Rahim, N. A. (2016). Backtracking search algorithm for solving economic dispatch problems with valve-point effects and multiple fuel options. *Energy*, *116*, 637–649. https://doi.org/10.1016/j.energy.2016.09.140
Naama, B., Bouzeboudja, H., & Allali, A. (2013). Solving the economic dispatch problem by using Tabu Search algorithm. *Energy Procedia*, *36*, 694–701. https://doi.org/10.1016/j.egypro.2013.07.080
Ouiddir, R., Rahli, M., & Abdelhakem-Koridak, L. (2005). Economic dispatch using a genetic algorithm: Application to western Algeria's electrical power network. *Journal of Information Science and Engineering*, *21*(3), 659–668.
Pattanaik, J. K., Basu, M., & Dash, D. P. (2019). Dynamic economic dispatch: a comparative study for differential evolution, particle swarm optimization, evolutionary programming, genetic algorithm, and simulated annealing. *Journal of Electrical Systems and Information Technology*, *6*(1), 1–18. https://doi.org/10.1186/s43067-019-0001-4
Pothiya, S., Ngamroo, I., & Kongprawechnon, W. (2008). Application of multiple tabu search algorithm to solve dynamic economic dispatch considering generator constraints. *Energy Conversion and Management*, *49*(4), 506–516. https://doi.org/10.1016/j.enconman.2007.08.012
Purlu, M., & Turkay, B. E. (2018). Dynamic economic dispatch with valve point effect by using GA and PSO Algorithm. *2018 6th International Conference on Control Engineering and Information Technology, CEIT 2018*, *October*, 25–27. https://doi.org/10.1109/CEIT.2018.8751770
Rezaie, H., Kazemi-rahbar, M. H., Vahidi, B., & Rastegar, H. (2019). Journal of Computational Design and Engineering Solution of combined economic and emission dispatch problem using a novel chaotic improved harmony search algorithm. *Journal of Computational Design and Engineering*, *6*(3), 447–467. https://doi.org/10.1016/j.jcde.2018.08.001
Salem, E., Mousa, H., & I., A. (2019). A Swarm-based Algorithm for Solving Economic Load Dispatch Problem. *International Journal of Computer Applications*, *177*(26), 11–18. https://doi.org/10.5120/ijca2019919719
Swain, R. K., Sahu, N. C., & Hota, P. K. (2012). Gravitational Search Algorithm for Optimal Economic Dispatch. *Procedia Technology*, *6*, 411–419. https://doi.org/10.1016/j.protcy.2012.10.049
Tofighi, M., Maddahi, R., & Sadeqzadeh, M. (2011). An improved genetic algorithm based economic dispatch with nonsmooth fuel cost function. *Proceedings of the 2011 International Conference on Electrical Engineering and Informatics*, *July*, 1–6. https://doi.org/10.1109/ICEEI.2011.6021722
Xin-gang, Z., Ji, L., Jin, M., & Ying, Z. (2020). An improved quantum particle swarm optimization algorithm for environmental economic dispatch. *Expert Systems with Applications*, *152*. https://doi.org/10.1016/j.eswa.2020.113370

Appendix

Table 5. Input data used to simulate the test system 1 model with six generators

Gen. Unit	**a**	**b**	**c**	**P_{min} (MW)**	**P_{max} (MW)**
1	0.0070	7.0	240	100	500
2	0.0095	10.0	200	50	200
3	0.0090	8.5	220	80	300
4	0.0090	11.0	200	50	150
5	0.0080	10.5	220	50	200
6	0.0095	12.0	190	50	120

Table 6. Input data used to simulate the test system 2 model with fifteen generators

Gen. Unit	a	b	c	P_{min} (MW)	P_{max} (MW)
1	0.000299	10.1	671	150	455
2	0.000183	10.2	574	150	455
3	0.001126	8.8	374	20	130
4	0.001126	8.8	374	20	130
5	0.000205	10.4	461	150	470
6	0.000301	10.1	630	135	460
7	0.000364	9.8	548	135	465
8	0.000338	11.2	227	60	300
9	0.000807	11.2	173	25	162
10	0.001203	10.7	175	25	160
11	0.003586	10.2	186	20	80
12	0.005513	9.9	230	20	80
13	0.000371	13.1	225	25	85
14	0.001929	12.1	309	15	55
15	0.004447	12.4	23	15	55