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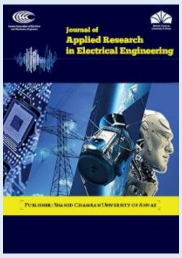

**Research Article**

# Combined Economic Emission Dispatch in a Grid-Connected Microgrid Using an Improved Mayfly Algorithm

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**Abstract: The Combined Economic Emission Dispatch (CEED) is an important consideration in every power system. In this paper, a modified Mayfly Algorithm named Modified Individual Experience Mayfly Algorithm (MIE-MA) is used to solve the CEED optimization problem. The modified algorithm enhances the balance between exploration and exploitation by utilizing a chaotic decreasing gravity coefficient. Additionally, instead of the MA relying solely on the best position, it calculates the experience of a mayfly by averaging its positions. The CEED problem is modeled as a nonlinear optimization problem constrained with four equality and inequality constraints and tested on a grid-connected microgrid that consists of four dispatchable distributed generators and two renewable energy sources. The performance of the MIE-MA on the CEED problem is compared to Particle Swarm Optimisation (PSO), an MA variant that incorporates a levy flight algorithm named IMA and Dragonfly Algorithm (DA) using the MATLAB R2021a software. The MIE-MA achieved the best optimum cost of 11306.6 $/MWh, compared to 12278.0 $, 12875.8$, and 17146.4$ of the DA, IMA, and PSO respectively. The MIE-MA also achieved the best average optimum cost over 20 runs of 12163.48 $, compared to 12555.36 $, 13419.67 $, and 17270.08 $ of the DA, IMA, and PSO respectively. The hourly cost curve of the MIE-MA was also the best compared to the other algorithms. The MIE-MA algorithm thus achieves superior optimal values with fewer iterations.**

**Keywords:** MIE-MA, mayfly algorithm, swarm intelligence, economic dispatch.

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## 1. Introduction

Optimal operations and effective planning of electric power generation systems are critical elements in electric power systems. Problems relating to controlling, operating, and economic dispatch of power generation resources are still being addressed [1]. Economic dispatch power generation resources are useful in finding the right balance between system performance and cost of operation [2, 3]. Traditionally, the effects of emissions due to power system operations were not considered in the economic dispatch problem. However, due to environmental concerns such as global warming and pollution, it has become necessary to add an emission cost component to the economic dispatch problem. This is collectively known as the Combined Economic Emission Dispatch (CEED), which aims to mitigate emission levels from all generating units and promotes the transition towards a sustainable and environmentally friendly power generation paradigm [3]. The addition of the emission component, and consideration of intermittent renewable sources in the CEED problem increases the complexity of the problem due to the increase non-convexity, increased constraints, and decision variables, increased computational time and the need for trade-off between emission levels and economic cost. The CEED presents a highly nonlinear optimization problem with constraints such as link capacity limits, ramp rate limits, load-demand constraints, and the generator's maximum capacity limit constraints and the non-convexity significantly introduces multiple local optima, making it difficult to find the optimal solution. Due to this complexity, it is inefficient to employ conventional mathematical and numerical methods to solve the CEED problem, due to their high tendency to get stuck at local optimum [4]. More sophisticated nature-inspired metaheuristic algorithms have been adopted to solve complex problems due to their effectiveness in achieving near-global or global solutions for complex nonlinear problems [5].

Metaheuristic algorithms, a computational intelligence paradigm, prove valuable in addressing such complex problems. They provide benefits including effortless application to continuous and discrete problems, convex and non-convex problems, reduced mathematical complexity, and effective search for global optimal solutions [6]. Over the years, metaheuristic algorithms have been applied to economic dispatch problems in microgrids. In [7] PSO was used to solve the CEED problem while considering demand response, uncertainty in load and RESs on a microgrid with four dispatchable DGs. In [8], Grasshopper Algorithm was used to solve the CEED problem in an IEEE system which has three thermal generators, the algorithm was shown to outperform FA and BA in achieving the CEED. In [9], Gravitational Search Algorithm (GSA) was used as an optimization tool to solve the CEED problem. The algorithm was shown to outperform the BBO algorithm in achieving the optimal CEED. In [10], Economic dispatch combined with emission dispatch was performed using the Crow Search Algorithm (CSA). CSA was shown to outperform PSO and GA in achieving the optimal CEED. The above algorithms still have issues with local stagnation and so researchers are coming up with new and improved algorithms to address these issues [11].

The Mayfly algorithm, one of the latest Swarm Intelligence Optimization Algorithms (SIOAs) is considered a promising algorithm and, it draws inspiration from the movement and mating behaviour of mayflies [12, 13]. It shows great promise with its improved capabilities in exploration and exploitation. It has been shown to outperform other algorithms such as PSO, Invasive Weed Optimisation (IWO), Bees algorithm (BA), GA, Differential Evolution (DE), Firefly Algorithm (FA), Harmony Search Algorithm (HSA), etc. MA has been successfully applied by researchers to tackle complex problems [13]. For instance, in [14], for agricultural unmanned aerial vehicles (UAVs), it was used to solve a 2D path planning problem. In reference [15], MA was applied to tackle the optimal power flow problem in regulated electricity markets. Moreover, the algorithm has demonstrated advancements in Maximum Power Point Tracking (MPPT) for photovoltaic systems [11].

However, MA does have certain limitations, including premature convergence and stagnation. As a result, further contributions are required to address these issues. Other researchers have made some attempts to address the above problems. A modified version of MA known as PGB-IMA was presented in reference [13]. This variant selected the global best from the entire mayfly population, including both males and females, to enhance exploration capabilities. While this enhancement proved effective for unimodal functions, it exhibited slower convergence or local optima entrapment on multimodal functions. In [12], levy flight was employed to improve exploration in the MA for solving the CEED problem. However, this approach occasionally caused mayflies to fly out of smaller search spaces. Researchers introduced ModMA in reference [14]. This approach incorporated various techniques, including adaptive Cauchy method, exponent decreasing inertia weight, an improved crossover operator and decreasing inertia weight, to achieve a balance between exploitation and exploration within the MA. ModMA improved the convergence rate but still faced the challenge of local optima trapping. Consequently, further improvements are necessary to address the issues of local optima entrapment and premature convergence, thus enhancing the overall performance of MA.

Therefore, this work proposes a modified MA that addresses the aforementioned deficiencies of the MA and consequently applies it to the CEED problem to obtain optimal results. The modification introduced in the algorithm focuses on individual experience, resulting in MIE-MA. This algorithm enhances mayfly movement to improve convergence rate and overcome local optima entrapment. This is achieved by replacing the personal best (pbest) in the original Mayfly Algorithm with personal experience (Pexp). Pexp is calculated as the average of all positions visited by a mayfly, ensuring equal contribution from all visited positions. This enables the mayflies to effectively explore their search spaces, avoiding premature stagnation and overlooking optimal solutions. As a result, the MIE-MA approach yields optimal solutions with fewer iterations. Additionally, the algorithm incorporates a chaotic decreasing gravity coefficient to strike a balance between exploration and exploitation. The innovation of this work lies in the modification of the mayfly algorithm by modifying the individual experience formula of the MA, adopting the chaotic decreasing gravity coefficient to the mayfly and applying it to a CEED problem in a grid-connected microgrid. The rest of the paper is structured as follows: Section 2 describes the problem formulation, Section 3 describes the mayfly algorithms, Section 4 contains the proposed MIE-MA, Section 5 illustrates the implementation of the MIE-MA on the CEED, Section 6 contains results and analysis and finally, Section 7 concludes the paper.

## 2. Problem Formulation

The CEED problem is modeled as a nonlinear constrained optimization problem with both equality and inequality constraints [7].

### 2.1. Decision Vector

For each hour, the decision vector consists of the power output of the dispatchable generators (DG) and the power exchanged with the upstream grid. i.e.

$$X = \left[P_{DG(1)}, \ldots, P_{DG(N),} P_{grid}\right]$$

where, $P_{DG}$ is power output of dispatchable generators, $N$ is the total number of dispatchable generators, and $P_{grid}$ is power exchange with upstream grid. $P_{grid}$ is positive when power is bought from the grid and negative when power is transferred to the upstream grid.

### 2.2. Objective Function

The cost of dispatchable DGs is denoted by equation (1), while their emission treatment cost is described by equation (2).

$$C_i(P_{DG,i}) = \alpha_i\left(P_{DG,i}\right)^2 + b_i P_{DG,i} + c_i \qquad \$/h \qquad (1)$$

$$em_i(P_{DG,i}) = d_i\left(P_{DG,i}\right)^2 + e_i P_{DG,i} + f_i \qquad \$/h \qquad (2)$$

$\alpha_i$, $b_i$, and $c_i$ are operational cost coefficients, and $d_i$, $e_i$, and $f_i$ are emission treatment cost coefficients for $CO_2$, $SO_2$ and $NO_x$, respectively.

The objective function includes the operation and emission costs, i.e.,

$$OF = \sum_{i=1}^{NG}\sum_{t=1}^{24} C_i\left(P_{DG,i}(t)\right) + \sum_{i=1}^{NG}\sum_{t=1}^{24} em_i\left(P_{DG,i}(t)\right) + \sum_{t=1}^{24}\rho(t)P_{grid}(t) + \sum_{t=1}^{24}\gamma P_{grid}(t) \quad (3)$$

where $\rho(t)$ is the market price at $t^{th}$ time, and $\gamma$ is the emission factor of power purchased from upstream grid at the $t^{th}$ time.

### 2.3. Constraints

The constraints are power balance constraints, output limit constraints, ramp rate limits and power transfer limits.

#### 2.3.1. Power balance

$$P_d(t) = P_{grid}(t) + \sum_{i=1}^{NG} P_{DG,i}(t) + \sum_{p=1}^{Nren} P_{renew,p}(t)$$

where $P_{renew,p}(t)$ is the power output of $P^{th}$ renewable DG unit at the $t^{th}$ time, and $Nren$ is the total number of renewable DGs.

#### 2.3.2. Output limits

The power output of each dispatchable DG must be within its output limits, i.e.

$$P_{DG,i,min} \le P_{DG,i}(t) \le P_{DG,i,max}$$

#### 2.3.3. Ramp rate limits

The gradient of change of the output of the DG must be limited, i.e.,

$$P_{DG,i}(t) - P_{DG,i}(t-1) \le RU_{DG,i}$$

$$P_{DG,i}(t-1) - P_{DG,i}(t) \le RD_{DG,i}$$

#### 2.3.4. Power transfer limits

To comply with the power flow limit of the link connecting the microgrid and the upstream grid, it is necessary to ensure that the following equation is met:

$$-P_{transf,max} \le P_{grid}(t) \le P_{transf,max}$$

## 3. MAYFLY ALGORITHM

The MA mimics the way mayflies fly and mate. It is a combination of the major pros of PSO [16], FA [17], and GA [18]. The MA consists of the following 6 phases [4]:

### 3.1. Initialisation

During this phase, a random set of male and female mayflies is generated. Each mayfly is assigned a current velocity ($v_i$) and position ($x_i$), denoted as $v_i = (v_{i1}, v_{i2}, ..., v_{in})$ and $x_i = (x_{i1}, x_{i2}, ..., x_{in})$, respectively. The positions of the mayflies are then adjusted using information from their best position (*pbest*) and the best position in the entire population (*gbest*).

### 3.2. Male Mayfly Movement

The position is updated by adding to the position, a velocity $v_i^{t+1}$. For male mayflies, the velocity is expressed as

$$v_{ij}^{t+1} = v_{ij}^t + a_1 e^{-\beta r_p^2}\left(pbest_{ij} - x_{ij}^t\right) + a_2 e^{-\beta r_g^2}\left(gbest_j - x_{ij}^t\right)$$

In the given equation, the visibility coefficient is denoted as $\beta$, and $a_1$ and $a_2$ represent positive constants representing attractionrefers to the best position attained by the male mayfly indexed as "$i$" in dimension "$j$". The variables "$r_p$" and "$r_g$" represent the Euclidean distances between the position "$x_i$" and the individual best position (*pbest*) and the global best position (*gbest*), respectively. $g$ is the gravity coefficient and is typically a fixed number ranging from 0 to 1.

### 3.3. Female Mayfly Movement

Female mayflies move towards male mayflies i.e. $y_i^{t+1} = y_i^t + v_i^{t+1}$, y denotes position of the female mayfly. For male mayflies, the velocity is expressed as:

$$v_{ij}^{t+1} = \begin{cases} g * v_{ij}^t + a_2 e^{-\beta r_{mf}^2}\left(x_{ij}^t - y_{ij}^t\right),\ if\ f(y_i) > f(x_i). \\ g * v_{ij}^t + f_l * r,\ iff(y_i) \le f(x_i). \end{cases}$$

The velocity and position of the $i$-th female mayfly in dimension $j$ at iteration $t$ are respectively represented by $v_{ij}^t$ and $y_{ij}^t$. The attraction constant is denoted as "$a_2$" and the visibility coefficient is represented by "$\beta$". The variable "$r_{mf}$" indicates the Euclidean distance between the female mayfly indexed as "$i$" and the male mayfly indexed as "$i$". The random walk coefficient, "$f_l$", signifies that a female may not be attracted to a male. Additionally, r represents a random value ranging from -1 to 1.

### 3.4. Mating Mayflies

This enhances exploration through communication between mayflies by producing offsprings $off_1$ and $off_2$. The crossover operator is used, i.e., $off_1 = r*m + (1-r) *f$ and $off_2 = r*f+(1-r) *m$, where $m$, $f$, and $r$ are male mayfly, female mayfly, and a random number between 0 and 1, respectively

### 3.5. Mutation of Mayflies

This enhances *the* exploitation of the MA. This is expressed as

$$offspring_n = offspring_n + \sigma N_n(0,1).$$

In this equation, $\sigma$ represents the standard deviation, while $N_n$ denotes the standard normal distribution.

### 3.6. Reduction of Nuptial Dance and Random Walk

This aids in striking a balance between exploitation and exploration. This is expressed as: $d_t = d_o\delta^t$, $0 < \delta < 1$ and $fl_t = fl_o\delta^t$, $0 < \delta < 1$, respectively.

In this equation, $t$ represents the iteration counter, and $\delta$ is a fixed value in the range of (0, 1).

### 3.7. Pseudocode of the Algorithm

The pseudocode of the algorithm is shown below:

- Define the objective function as $f(x)$, where x represents the vector $(x_1, ..., x_d)^T$.
- Set the initial positions and velocities for the male population of mayflies.
- Set the initial positions and velocities for the female population of mayflies.
- Evaluate the solutions and determine the global best solution (gbest).

- **Do while** iteration<maximum iterations
  - Adjust the velocities and positions of both sets of mayflies.
  - Solve their objective function values.
  - Separate mayflies based on their objective function value.
  - Enable mating amongst them.
  - Use crossover operator to produce offspring.
  - Assign genders (male and female) to offspring randomly.
  - Do a replacement of worst solutions with best solutions.
  - reassign the personal best (*pbest*) and global best (*gbest*) solutions with their latest values.
- **End while**
- Show the final results.

## 4. Modified Individual Experience Mayfly Algorithm

In the original Mayfly Algorithm (MA), each mayfly's position is adjusted based on its individual experience (*pbest*) and the experience of its neighbours. However, this approach may limit the contribution of mayflies that are consistently moving at a better rate than the global best (*gbest*), potentially leading to stagnation if the *gbest* is trapped in a local optimum.

To address this issue, a modification is proposed. In this modified approach, the experience of a mayfly is calculated as the average of the positions it has visited in the search space. This enhanced representation provides a better understanding of how the mayflies are approaching the global optimum and ultimately yields optimal values in the search space. The formulation for this modification is as follows:

$$P_{exp,i}^{t} = \frac{\sum_{t=1}^{iter} x_i^t}{iter} \qquad (4)$$

where, $P_{exp,i}^{t}$ is mayfly $i$-th experience at step $t$, $iter$ is iteration number at current step, and $x_i^t$ is mayfly $i$-th position at step $t$.

To enhance the balance between exploration and exploitation in the Mayfly Algorithm (MA), a strategy of adopting a chaotic random decreasing gravity coefficient is implemented. This strategy is motivated by a study [5] that explored different weight strategies in Particle Swarm Optimization (PSO) and their impact on the algorithm's performance. The study found that a chaotic random decreasing inertia weight strategy yielded the highest accuracy. This strategy enables alternating between rough and fine search in all evolutionary processes [6].

In this work, a slightly modified version of the chaotic random decreasing inertia weight strategy is utilized. The formulation for this strategy is as follows:

$$g = (gmax - gmin) * \left(\frac{MaxIt - iter}{MaxIt}\right) + gmin * z \qquad (5)$$

$$z = 4 * z * (1 - z)$$

where *gmax* and *gmin* represent the maximum and minimum inertia weights, respectively, and *z* is a number randomly picked between 0 and 1.

## 5. Implementation of the MIE-MA on the CEED

The studied grid connected microgrid consists of four dispatchable DGs (MTs) and two renewable energy sources as shown in Fig. 1 [7, 19].

The data used in this research consists of the operational characteristics of four dispatchable DGs (micro-turbines), day ahead power forecasts of the two renewable energy sources and the grid price for each hour. The data was obtained from [7]. Table 1 and Table 2 in the Appendix represent the utilized data.

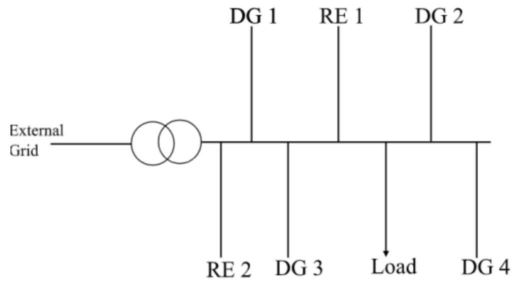


**Fig. 1:** Diagram of the studied system.

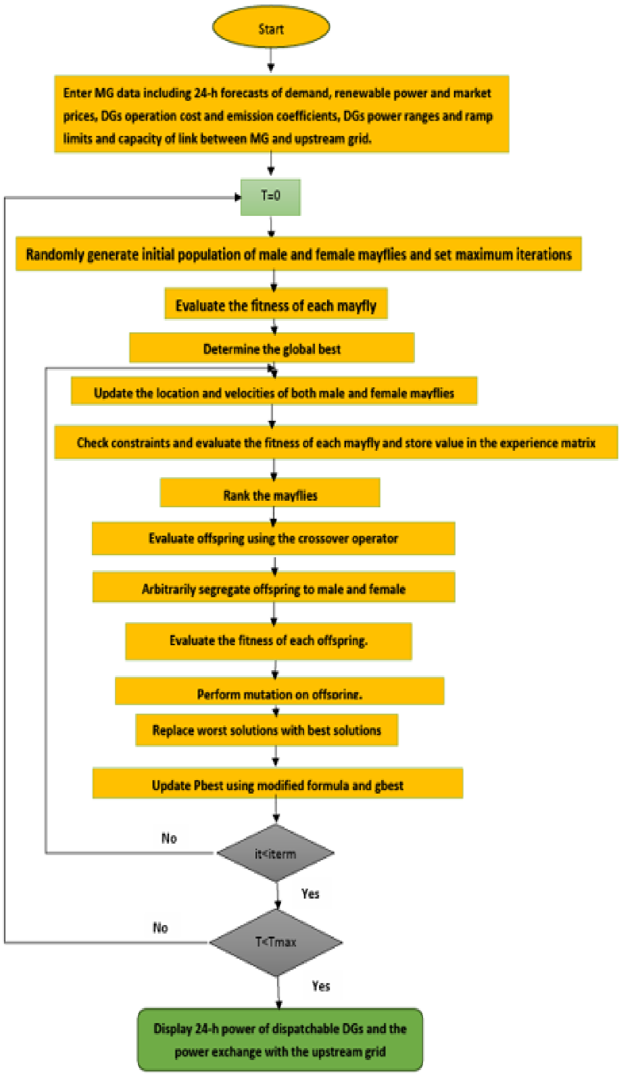


**Fig. 2:** Flowchart of the Implementation method.

According to [19], for Micro-Turbines (MT), the emission of $CO_2$, $SO_2$ and $NO_x$ are 0.7239, 0.0036 and 0.1994 kg/MWh respectively. For a macro grid, the emissions of $CO_2$, $SO_2$ and $NO_x$ are 0.8891, 1.8016 and 1.6021 kg/MWh respectively. The treatment cost for $CO_2$, $SO_2$ and $NO_x$ are 0.0311, 2.1999 and 9.3332 $/kg, respectively [7]. Therefore $d_i = f_i = 0$, $e_i = 1.8620$, and $\gamma = 18.9161$.

The optimal parameters for MIE-MA include maximum iterations=100, male and female population = 200 (each one), $a_1 = 1$, $a_2 = 1.5$, $\beta = 2$, $d = 0.1$, $f_l = 0.1$, $g = 0.8$, $\delta = 0.77$, $gmax = 0.9$, and $gmin = 0.2$.

## 6. Results and Discussion

This section contains the results from the application of the MIE-MA on the CEED problem compared to a variant of the MA (IMA) [11] which incorporates levy flight algorithm, PSO and DA. The comparison parameters are optimum cost, average cost and standard deviation over 20 individual runs and hourly cost curves.

### 6.1. Optimum Cost Value

Table 3 shows the lowest value of the objective function obtained by each algorithm. It can be observed from the results above that the MIE-MA achieved the best optimal cost compared with PSO, DA and IMA, this is due to the superior exploration and exploitation abilities of the MIE-MA.

### 6.2. Mean Cost Values Standard Deviation

Table 4 shows the average optimum cost over 20 runs obtained by the various algorithms. It can be observed from the table above that the MIE-MA achieved the best average cost and standard deviation over 20 independent runs. This further shows the accuracy and consistency of the MIE-MA over the other algorithms.

### 6.3. Hourly Cost Curves and Convergence Curve

Fig. 3 illustrates the optimum cost of the objective function at each hour. It can be observed from the curves that for each hour, the MIE-MA consistently achieves a lower objective function value than the other algorithms. The convergence curve in Fig. 4 also shows the optimal cost achieved for each iteration in the final hour. The MIE-MA converged to its final value before the 700$^{th}$ iteration.

### 6.4. Dispatch of DGs and Exchanged Power

Table 5 shows the 24-hour dispatch results for the grid connected microgrid after the application of the modified individual experience mayfly algorithm. The negative values indicate a sale of power to the external grid. It can be observed from the dispatch that the power balance constraints, link capacity constraints, ramp rate limits and DG capacity limits are all respected. Furthermore, the dispatch indicates an effective sale of about 10.6MW over 24 hours to the external grid and for hours where the prices were higher (hours 12 to 24- see appendix), the dispatch indicates an effective sale of about 18.5 MW. This represents extra money for the MG to offset some of its operation and emission treatment costs.

**Table 3:** Optimum cost values of the various algorithms.

| Algorithm | Optimum Value ($) |
|---|---|
| MIE-MA | **11306.6** |
| ModLMA | 12875.8 |
| PSO | 17146.4 |
| DA | 12278.0 |

**Table 4:** Average optimum cost and standard deviation over 20 runs.

| Algorithm | Average Value ($) | Standard Deviation |
|---|---|---|
| MIE-MA | **12163.48** | **235.85** |
| IMA | 13419.67 | 323.69 |
| PSO | 17270.08 | 445.62 |
| DA | 12555.36 | 277.75 |

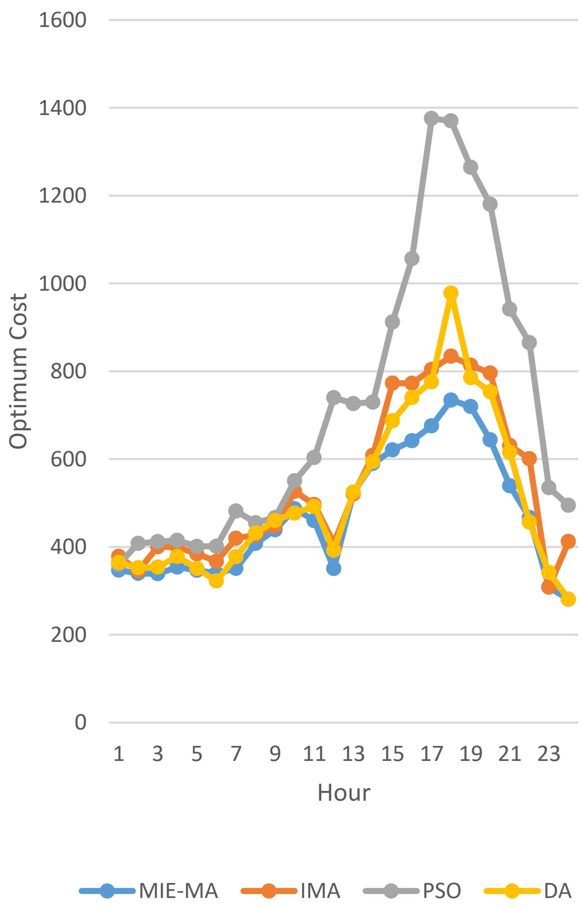


**Fig. 3:** Hourly cost curves.

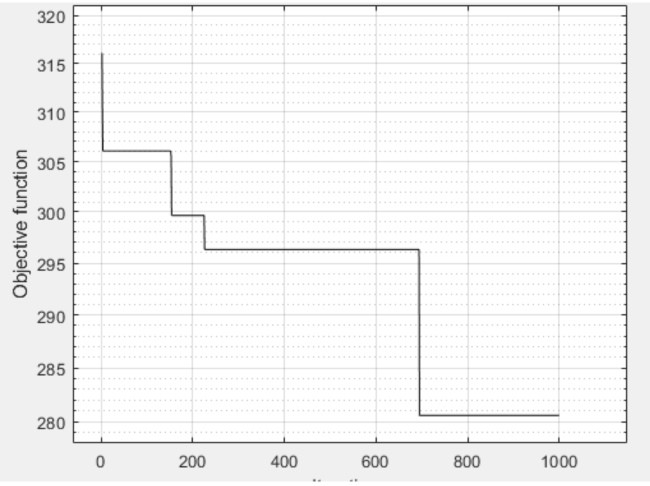


**Fig. 4:** Convergence curve of the MIE-MA in solving the CEED.

**Table 5:** Dispatch of DGs.

| T | $P_{DG,1}$ (MW) | $P_{DG,2}$ (MW) | $P_{DG,3}$ (MW) | $P_{DG,4}$ (MW) | $P_{Grid}$ (MW) |
|---|---|---|---|---|---|
| 1 | 3.852 | 1.2083 | 1.0626 | 0.8104 | 1.7969 |
| 2 | 1.2509 | 1.3581 | 0.9457 | 1.0152 | 3.9703 |
| 3 | 1.9208 | 1.2048 | 0.8068 | 0.9873 | 3.5505 |
| 4 | 4.3311 | 1.6524 | 0.8028 | 0.9074 | 1.3366 |
| 5 | 5 | 1.6675 | 1.1183 | 1.1321 | -0.4604 |
| 6 | 4.813 | 3.6753 | 1.401 | 1.0374 | -2.7628 |
| 7 | 4.8629 | 4.9925 | 1.496 | 0.9214 | -2.7726 |
| 8 | 4.9768 | 3.9284 | 1.0741 | 0.8172 | -0.5763 |
| 9 | 3.8179 | 1.8088 | 1.0172 | 0.9024 | 3.0957 |
| 10 | 4.5615 | 3.2682 | 1.6244 | 1.0409 | 0.9612 |
| 11 | 4.7876 | 4.9833 | 0.9646 | 0.9939 | -0.2693 |
| 12 | 4.8209 | 5 | 2.6222 | 2.1431 | -3.5097 |
| 13 | 4.6665 | 4.553 | 2.9348 | 1.9861 | -1.4302 |
| 14 | 4.7749 | 4.9937 | 2.6383 | 1.919 | -0.6257 |
| 15 | 4.9885 | 4.6034 | 2.8459 | 2.3223 | -0.6299 |
| 16 | 4.795 | 4.5757 | 2.9824 | 2.5704 | -0.5134 |
| 17 | 4.9654 | 4.7553 | 2.7354 | 2.8849 | -0.2609 |
| 18 | 4.9627 | 4.3054 | 2.9717 | 2.8497 | 0.2308 |
| 19 | 4.9167 | 4.774 | 2.2574 | 2.1228 | 0.7963 |
| 20 | 4.7373 | 4.6856 | 2.8315 | 2.9606 | -0.6249 |
| 21 | 4.9526 | 4.8529 | 2.8159 | 2.1956 | -1.3868 |
| 22 | 4.9985 | 4.6579 | 2.7469 | 2.1934 | -2.1666 |
| 23 | 4.8887 | 4.4929 | 2.0285 | 2.328 | -3.9179 |
| 24 | 4.8532 | 4.8041 | 2.5814 | 1.643 | -4.4316 |

### 6.5. Operation and Emission Costs

Table 6 represents the operation and emission treatment costs. Negative values indicate a profit. It can be observed that some gains are made in the emission treatment costs to offset some of the operational costs, leading to an overall lower CEED cost.

**Table 6:** Hourly operation and emission treatment costs.

| T | Operation Cost ($/h) | Emission Treatment Cost($/h) |
|---|---|---|
| 1 | 300.25 | 46.9 |
| 2 | 256 | 83.62 |
| 3 | 262.68 | 76.33 |
| 4 | 314.5 | 39.61 |
| 5 | 338.86 | 7.9 |
| 6 | 371.82 | -31.92 |
| 7 | 380.69 | -29.6 |
| 8 | 398.91 | 9.21 |
| 9 | 366.19 | 72.61 |
| 10 | 449 | 37.73 |
| 11 | 443.16 | 16.75 |
| 12 | 389.93 | -39.23 |
| 13 | 524.8 | -0.73 |
| 14 | 574.99 | 14.84 |
| 15 | 605.29 | 15.57 |
| 16 | 623.73 | 18.08 |
| 17 | 651.91 | 23.64 |
| 18 | 701.89 | 32.47 |
| 19 | 678.45 | 41.27 |
| 20 | 627.2 | 16.52 |
| 21 | 537.85 | 1.36 |
| 22 | 480.67 | -13.81 |
| 23 | 356.76 | -48.54 |
| 24 | 338.58 | -57.98 |

## 7. Conclusion

A modified Mayfly Algorithm has been developed, known as the Modified Individual Experience Mayfly Algorithm (MIE-MA). This algorithm incorporates changes to the individual experience of each mayfly and enhances the balance between exploitation and exploration capabilities. The MIE-MA has been applied to a CEED problem with four constraints. The considered grid-connected microgrid consists of four dispatchable DGs and two renewable DGs. The MIE-MA achieved the best optimum cost of 11306.6 $, compared to DA, IMA and PSO. This is an indication of the MIE-MA's superior exploitation-exploration balance. The MIE-MA also achieved the best average optimum cost and standard deviation over 20 runs of 12163.48 $ and 235.85$ compared to DA, IMA, and PSO. This is an indication of the superior accuracy and consistency of the MIE-MA over the other algorithms. The hourly cost curve also showed that the MIE-MA almost always outperformed the other algorithms in each hour. The MIE-MA can still be improved further by further enhancing its exploitation abilities and so future works should look at enhancing the MIE-MA or applying the MIE-MA to other engineering problems.

## CRediT Authorship Contribution Statement

**Nicholas Kwesi Prah II:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Software, Visualization, Roles/Writing - original draft, Writing - review & editing. **Elvis Twumasi:** Conceptualization, Investigation, Methodology, Supervision, Validation, Visualization, Roles/Writing - original draft, Writing - review & editing. **Emmanuel Asuming Frimpong:** Investigation, Methodology, Supervision, Validation, Visualization, Roles/Writing - original draft, Writing - review & editing.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues; including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy has been completely observed by the authors.

## Appendix

**Table 1:** Operational parameters of the DGs

| | DG1 | DG2 | DG3 | DG4 |
|---|---|---|---|---|
| α ($/MWh) | 0.03 | 0.025 | 0.02 | 0.02 |
| b ($/MWh) | 27.7 | 39.1 | 61.3 | 65.6 |
| c($) | 0 | 0 | 0 | 0 |
| Minimum Power (MW) | 1 | 1 | 0.8 | 0.8 |
| Maximum Power (MW) | 5 | 5 | 3 | 3 |
| Ramp-up limits (MW) | 2.5 | 2.5 | 3 | 3 |
| Ramp-down limits (MW) | 2.5 | 2.5 | 3 | 3 |

**Table 2:** Day-ahead demand, renewable output and grid price.

| Hour | Demand (MW) | Renewable #1(MW) | Renewable #2(MW) | Grid price ($/MWh) |
|---|---|---|---|---|
| 1 | 8.73 | 0 | 0 | 15.3 |
| 2 | 8.54 | 0 | 0 | 10.97 |
| 3 | 8.47 | 0 | 0 | 13.51 |
| 4 | 9.03 | 0 | 0 | 15.36 |
| 5 | 8.79 | 0.63 | 0 | 18.51 |
| 6 | 8.81 | 0.8 | 0 | 21.8 |
| 7 | 10.12 | 0.62 | 0 | 37.06 |
| 8 | 10.93 | 0.71 | 0 | 22.83 |
| 9 | 11.19 | 0.68 | 0 | 21.84 |
| 10 | 11.78 | 0.35 | 0 | 27.09 |
| 11 | 12.08 | 0.62 | 0 | 37.06 |
| 12 | 12.13 | 0.36 | 0.75 | 68.95 |
| 13 | 13.92 | 0.4 | 0.81 | 65.79 |
| 14 | 15.27 | 0.37 | 1.20 | 66.57 |
| 15 | 15.36 | 0 | 1.23 | 65.44 |
| 16 | 15.69 | 0 | 1.28 | 79.79 |
| 17 | 16.13 | 0.05 | 1 | 115.45 |
| 18 | 16.14 | 0.04 | 0.78 | 110.28 |
| 19 | 15.56 | 0 | 0.71 | 96.05 |
| 20 | 15.51 | 0 | 0.92 | 90.53 |
| 21 | 14.00 | 0.57 | 0 | 77.38 |
| 22 | 13.03 | 0.60 | 0 | 70.95 |
| 23 | 9.82 | 0 | 0 | 59.42 |
| 24 | 9.45 | 0 | 0 | 56.68 |

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