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Optimal Economic Dispatch Using Mayfly Optimization Algorithm in Sulbagsel Electricity System with Integrated Renewable Energy Sources

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Abstract: This study focuses on optimizing generation costs for thermal power plants in the Southern Sulawesi (Sulbagsel) electricity system by incorporating Renewable Energy Sources (RESs). The Improved Mayfly Algorithm (IMA), inspired by the mating and flight behaviors of adult mayflies and enhanced with Exponent Decreasing Inertia Weight (EDIW) to adjust inertia variations, is applied to minimize generation costs. The effectiveness of the proposed IMA is evaluated through comparisons with other methods, such as the Quadratic Time Optimization (QTO) and the standard MA. Statistical analysis of the benchmarking results demonstrates that IMA outperforms comparable other algorithms. For the first case, mid-day peak load, the optimization results show that QTO reduces costs by 24.24%, MA by 24.25%, and the proposed IMA by 24.28%. In the second case, nighttime peak load, the cost reductions achieved are 25.96% for QTO, 26.28% for MA, and 26.72% for IMA.

Keywords: Economic dispatch, Sulbagsel system, Swarm intelligence, Improved mayfly algorithm, Cost.

1. Introduction

Economic dispatch (ED) is one of the most critical tasks in the design and management of electric power systems. The primary goal of ED is to schedule the output of generating units to meet load demand at the lowest possible cost while satisfying the operational constraints of both the units and the system. Improvements in unit output scheduling can lead to substantial cost savings. Typically, ED prioritizes the use of the most efficient generators, which helps to reduce both fuel costs and carbon emissions [1]. Several methods are available for solving ED, including lambda iteration [2], Newton [3], gradient [4], linear programming [5], and base point and participation factor methods [6]. However, various constraints can render the ED problem non-convex [7], emphasizing the need for advanced intelligent methods to effectively manage these complexities.

Swarm Intelligence is an artificial intelligence technique based on collective behavior. Swarm intelligence techniques are being increasingly employed to address ED issues. An ED issue for a hybrid power system with 40 thermal generators is optimized using the salp-swarm algorithm (SSA) [8]. Paper [9] presents an ED model based on the enhanced krill swarm optimization algorithm (IKSO) for an integrated energy system comprising photovoltaic, wind, and grid sources. In another study, an improved artificial bee colony (IABC) is proposed to address the ED problem in three large-scale test systems [10]. The work presented in [11] addresses the ED problem using the artificial fish swarm algorithm (AFSA) on five standard test systems consisting of generating units. Additionally, the performance of the chameleon swarm algorithm

(CSA) in solving the ED problem for four conventional power units is discussed in [12]. While these studies demonstrate promising results with swarm intelligence methods, many primarily rely on test cases to evaluate the effectiveness of the proposed algorithms.

The Southern Sulawesi (Sulbagsel) electricity system, formerly known as Sulselrabar, is located in the Sulawesi province of Indonesia [13]. Operating at a voltage of 150 kV and 57 transmission lines [14]. Research focused on optimizing ED in the Sulbagsel electricity system has been conducted. For example, in [15], the horse herd optimization (HHO) method is introduced to minimize thermal generation costs in the Sulbagsel system, specifically in a mid-day peak load case study. A modified improved PSO (MIPSO) algorithm is proposed in [16] and compared with the Lagrange method, applied to the Sulselrabar system prior to the recent incorporation of RESs. Furthermore, the ACO method is employed in [17] to tackle the ED problem for the 150 kV Sulselrabar electrical system. Given the existing research on ED in the Sulbagsel electricity system, further analysis is warranted to investigate ED systems integrated with RESs, which is relevant to the current configuration of the Sulbagsel electricity system. This serves as the primary motivation for examining optimal ED in the actual Sulbagsel electricity system with RESs, utilizing the latest available data. In this study, the power generation of the Sulbagsel electricity system includes 9 thermal units, 5 hydro power plants (HPPs), and 1 wind power plant (WPP).

The mayfly algorithm (MA) is a swarm intelligence-based optimization technique [18], inspired by the flight patterns and mating behaviors of mayflies. It combines the strengths of both swarm intelligence and evolutionary algorithms. The mating dance and random flight behaviors enhance the algorithm's ability to balance exploration and exploitation, helping to avoid local optima. In [19], the performance of seven advanced metaheuristic optimization algorithms is evaluated across 25 test functions, categorized into three types: unimodal, multimodal, and fixed-dimension. However, the standard MA has limitations that hinder its application to high-dimensional, nonlinear complex problems, such as feature selection [18]. One way to enhance the performance of swarm intelligence algorithms is by adjusting the inertia weight [20]. This study introduces the Improved MA (IMA), which incorporates an Exponent Decreasing Inertia Weight (EDIW) strategy to enhance both exploration capabilities and convergence speed compared to the standard MA. The EDIW strategy accelerates individual convergence and has been successfully applied to other swarm intelligence techniques, improving their performance [21].

The application of the MA for ED optimization has been explored in various studies. In [22], MA is proposed for solving the ED problem in microgrids, where the test case includes thermal power generation units, solar power, and wind power. Similarly, in [23], ED optimization is examined in a system that integrates thermal power generation units, wind turbines, photovoltaic panels, and energy storage devices. Based on the research into MA applications for ED problems, a comprehensive study on real systems is essential to ensure optimal implementation. Additionally, performance improvements with the IMA need to be explored for applications in large-scale systems. This provides our second motivation: to investigate the IMA's effectiveness in minimizing generation costs for the Sulbagsel electricity system integrated with RESs, focusing on peak load case studies during midday and nighttime.

The main contributions of this study are as follows:

1) Investigating optimal ED for a real Sulbagsel electricity system integrated with RESs using the most recent data updates. This includes considering generation limits, ensuring that the load demand can be met, and applying both equality and inequality constraints.
2) Implementing IMA to minimize generation costs, optimizing the composition of RESs, and reducing system losses for Sulbagsel electricity through case studies focusing on peak loads during mid-day and nighttime.

The remainder of this paper is organized as follows: Section II summarizes the ED and the case system, Section III outlines the research methodology of the study, Section IV presents the results, and Section V concludes the study.

2. Economic dispatch problem

This section covers the development of ED theory and the test systems used in this study.

2.1 Economic dispatch

An electrical power system consists of multiple generating units. It is important to recognize that transmission losses occur, even if they may be negligible when powering nearby generators. When transmission losses are ignored, the costs of fuel use and power generation can be calculated using Eq. (1) until Eq. (3) [24].

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$$F_T = F_a P_a + F_b P_b + F_c P_c \quad (1)$$

$$P_R = P_r \quad (2)$$

$$P_T = P_a + P_b + P_c \quad (3)$$

Here, P_T represents the total output power of the generators (MW), P_R denotes the system load (MW), and F_T indicates the fuel consumption (Rp/hr). The input-output (IO) characteristics of thermal generators reveal that as output power increases, fuel costs also rise. These attributes are expressed in Eq. (4).

$$H_n = \alpha_n + \beta_n P_n + \gamma_n P_n^2 \quad (4)$$

The fuel input of the generator is represented by H_n (L/hr), and and its output by P_n (MW). The IO coefficients for the *n-th* generator are constants α_n, β_n, and γ_n. These figures must be determined using the unique output power data and fuel cost characteristics of each generator. Based on the observed values, a functional relationship is determined by analyzing the data using the least squares regression method.

Each generator's capacity is considered in the ED solution, where both equality and inequality constraints must be addressed to ensure optimal operation. The equality constraint ensures that the total power generated by all generators meets the load demand plus transmission losses, as stated in Eq. (5). Although the output power of each generator in the system varies, loss coefficients can be regarded as constant [25].

$$\sum_{i=1}^{N} P_i = P_R + P_L \quad (5)$$

In this context, P_R represents the total load (MW), P_L denotes the transmission losses (MW), and P_i is the generator's output power (MW). The generator's output power is maintained within preset limitations by an inequality constraint that prevents it from falling below the minimum or rising above the maximum permitted power. This constraint is represented by Eq. (6) and Eq. (7).

$$P_{i\,min} \leq P_i \leq P_{i\,max} \quad (6)$$

Table 1. Numbering of sulbagsel system generations

Bus	Name-Type	Bus	Name-Type
1	Bakaru-Slack	24	Bontoala-Load
2	Pinrang-Gen	25	Panakukkang-Load
3	Suppa-Gen	26	Tanjung Bunga-Load
4	Tello-Gen	27	Sungguminasa-Load
5	Borongloe-Gen	28	Talasa-Load
6	PLTUjnpto-Gen	29	Jeneponto-Load
7	PLTUpngya-Gen	30	Bulukumba-Load
8	PLTUbsw-Gen	31	Bone-Load
9	Bantaeng-Gen	32	Soppeng-Load
10	Sinjai-Gen	33	Sidrap-Load
11	WPPsidrap-Gen	34	Maros-Load
12	Sengkang -Gen	35	Bolangi-Load
13	Palopo-Gen	36	Enrekang-Load
14	Makale-Gen	37	Siwa-Load
15	Mamuju-Gen	38	Pangkep70-Load
16	Polmas-Load	39	Tonasa-Load
17	Majene-Load	40	Mandai-Load
18	Pare-Pare-Load	41	Daya-Load
19	Barru-Load	42	Tello70-Load
20	Pangkep-Load	43	Tello Lama70-Load
21	Bosowa-Load	44	Bontoala 70-Load
22	Kima-Load	45	Tello30-Load
23	Tello Lama-Load	46	Barawaja-Load

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{j=1}^{N} B_{i0} P_j + B_{00} \quad (7)$$

Here, B_{i0} and B_{00} are loss-related constants, while B_{ij} represents the loss coefficients. It is assumed that the loss coefficients remain constant, regardless of variations in output power.

2.2 Sulbagsel electricity system

The Sulbagsel system operates at a voltage of 150 kV and consists of nine thermal generators and six RES generators [26]. The numbering of the buses in the Sulbagsel system is presented in Table 1 [27].

3. Research method

This section describes the formulation of the proposed strategy and the objective function.

3.1 Mayfly algorithm (MA)

The study highlights the unique behavior of mayflies, a species with a lifespan of only twenty-four hours. Researchers have observed a distinct difference between male and female mayflies, with males consistently achieving higher optimization levels due to their inherent strength advantage. This trait parallels PSO, where individuals, like mayflies, update their positions $x_i(t)$ and velocities $v_i(t)$ based on their current state.

3.1.1. The action of male mayfly

Eq. (8) demonstrates that, within the MA framework, male mayflies adjust their positions based on their individual velocities. In this context, x_i represents the position of male mayfly i at the current time step t in the search space.

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{8}$$

During the iterative process described in [28], the male mayfly performs both exploration and exploitation tasks. When updating its velocity, the mayfly considers its most recent fitness value, $f(x_i)$, as well as the best fitness value observed along its previous trajectory, $f(x_{hi})$. Specifically, if $f(x_i)$ surpasses $f(x_{hi})$, the male mayfly adjusts its speed. This adaptive speed adjustment enables the male mayfly to refine its movement strategy when detecting an improvement in fitness. The process is mathematically formulated in Eq. (9).

$$v_i(t+1) = g.v_i(t) + a_i e^{-\beta r_p^2}[x_{hi} - x_i(t)] + a_2 e^{-\beta r_g^2}\left[x_g - x_i(t)\right] \tag{9}$$

The described process involves the gradual linear reduction of the variable g from its maximum to minimum values, controlled by the weight-balancing parameters a_1, a_2, and β. The variables r_p and r_g are used to compute the Cartesian distance between individuals and their historically best positions within the swarm. Specifically, Eq. (10) calculates the Euclidean distance in Cartesian space, quantifying the distance between individuals and their historically optimal locations within the swarm.

$$\left|\left|x_i - x_j\right|\right| = \sqrt{\sum_{k=1}^{n}\left(x_{ik} - x_{jk}\right)^2} \tag{10}$$

The male mayfly uses a random dance coefficient, denoted as d, to update its speed from the current value when the fitness value $f(x_i)$ is less than $f(x_{hi})$, as specified in Eq. (11). A uniformly distributed random number in the interval [-1, 1] is denoted by the symbol r_i.

$$v_i(t+1) = g(v_i(t) + d.r_i \tag{11}$$

3.1.2. The action of female mayfly

Female mayflies exhibit different behaviors compared to males. Instead of congregating, they actively seek out males to mate. Since $y_i(t)$ represents the current position of the female mayfly in the search space at time step t, Eq. (12) can be utilized to update its position by adding the velocity $v_i(t+1)$ to the current position, as follows:

$$y_i(t+1) = y_i(t) + v_i(t+1) \tag{12}$$

As discussed in [28], female mayflies adjust their speed based on the traits and behavior of the selected male mayfly.

If $f(y_i) > f(x_i)$, the i-th female mayfly will use Eq. (13) to update its speed. The Cartesian distance between the female mayfly and the chosen male mayfly is represented by r_m in this equation, while the speed is adjusted by an additional constant a_3.

$$v_i(t+1) = g.v_i(t) + a_3 e^{-\beta r_{mf}^2}[x_i(t) - y_i(t)] \tag{13}$$

When $f(y_i) < f(x_i)$, the female mayfly adjusts its speed using a different random dance coefficient, denoted as fl. As shown in Eq. (14), r_2 represents a randomly generated value within the range [-1, 1].

$$v_i(t) = g.v_i(t) + fl.r_2 \tag{14}$$

3.1.3. Mayflies mating

Each female mayfly, along with most male mayflies, engages in mating, resulting in the production of offspring. These offspring undergo random evolutionary changes and inherit traits from their parents, as described by Eq. (15) and Eq. (16). In this case, L, representing a set of random integers, is composed of values derived from a Gaussian distribution.

$$offspring1 = L * male + (1 - L) * female \tag{15}$$

$$offspring2 = L * female + (1 - L) * male \tag{16}$$

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3.1.4. Mayflies variation

To address the potential issue of early convergence, where the optimal value might be a local rather than a global optimum, we incorporated a normally distributed random number into the mutation process for mayfly offspring. The mutation formula for the mayfly offspring is outlined in Eq. (17).

$$offspring_n = offspring_n + \sigma . N(0,1) \quad (17)$$

In this context, $N(0, 1)$ denotes a standard normal distribution with a mean of zero and a variance of one, while σ represents the standard deviation of the normal distribution. The estimated number of mutant individuals is approximately 5% of all male mayflies, rounded to the nearest whole number.

3.1.5. Improved Mayfly Algorithm (IMA)

This section proposes the IMA, which incorporates the EDIW strategy to enhance both the exploration capabilities and convergence speed of the standard MA. A larger inertia weight during the initial phases facilitates broader particle exploration, allowing particles to search a larger space, while a smaller inertia weight in later phases supports particle exploitation. This paper introduces the EDIW into the MA, as presented in Eq. (18).

$$g = g_{min} + exp\left(1 - \frac{iter_{max}}{iter_{max} - iter + 1}\right) * (g_{max} - g_{min}) \quad (18)$$

For comparison, the latest intelligence methods based on Quadratic Time Optimization (QTO) [29] and the standard MA are utilized. Table 2 provides the parameter settings of MA.

Table 2. MA Parameters

Name	Parameter
MA	g=0.2, a_1=1, a_2=a_3=1.5, d=5, b=2, fl=1
IMA	g_{max}=0.9, g_{min}=0.2, a_1=1, a_2=a_3=1.5, d=5, b=2, fl=1

3.2 Objective function

The algorithms utilize Eq. (19) to determine the most economical generation combination. The first step in this process is to calculate the IO characteristics of the generators [30].

$$C_t = \sum_{i=1}^{n_g} \alpha_i + \beta_i P_i + \gamma_i P_i^2 \quad (19)$$

The generator must operate within its capacity limits to ensure stable performance [31]. Consequently, the equality constraint, as stated in Eq. (20), must limit the power output of the generator. Furthermore, as shown in Eq. (21) [31], it must adhere to the bounds established by the inequality constraint [32].

$$\sum_{i=1}^{n_g} P_i = P_D \quad (20)$$

$$P_{i_{min}} \leq P_i \leq P_{i_{max}} \quad (21)$$

4. Results and discussion

The experiment is carried out using MATLAB 2023b, with the following device specifications: an Intel Core i7-10870H-CPU @ 2.20GHz (16 cores), SSD storage consisting of a 512 GB Micron SSD and a 512 GB V-Gen SSD, 32 GB DDR4 RAM configured in dual-channel mode, and an NVIDIA GTX 1650 4 GB.

This section discusses the application of the IMA to optimize generation costs in the Sulbagsel electricity system, which is integrated with RESs. To evaluate the IMA's performance, mid-day and nighttime peak load case studies are used. The calculation begins by determining the cost function based on IO characteristics, with results presented in Table 3. Before implementing the IMA, a benchmarking analysis is conducted to compare the proposed method with similar intelligence algorithms, assessing each algorithm's performance based on the objective function.

4.1 Cost function

The first step in the computation process is to determine the IO characteristics of the thermal generators. These characteristics are then used in the IO equation, which is multiplied by the fuel price to derive the fuel cost equation. Table 3 [17] provides a comprehensive analysis of the data, including the IO characteristics and cost functions for each thermal generator in the Sulbagsel electrical system.

Tabel 3. Thermal power plant cost function

Unit	IO Equation (L/Hr)
Suppa	42642000 + 3679160P + 8240P^2
Agrekko/T.Lama	15902685 + 3296000P + 56437.82P^2
Jeneponto	57795360 + 5182960P - 2467.056P^2
PNGYA	11494800 + 3594700P + 28325P^2
BSW	68319900 + 444960P + 233671.98P^2
Bantaeng	12723075 + 9831350P - 85834.02P^2
Sengkang	14708400 + 11688440P - 67858.46P^2
Palopo	2132100 + 2315440P + 1030000P^2
Mamuju	12967185 + 3631780P + 98987.12P^2

4.2 IMA benchmarking

A benchmark analysis is conducted to assess the performance of the IMA method in comparison to the QTO and MA methods before applying it to optimization. The purpose of this analysis is to evaluate each method's exploration and exploitation capabilities. Table 4 presents six benchmark test functions. The unimodal functions *(f_1-f_2)* evaluate the algorithm's exploitation performance, while the multimodal functions *(f_3-f_4)* assess its exploration performance. This two-pronged approach offers a comprehensive evaluation of the algorithm across various optimization tasks. Additionally, the fixed-dimensional multimodal functions *(f_5-f_6)* examine the algorithm's ability to handle low-dimensional optimization settings. Table 5 presents the best results after 30 runs of the IMA, along with the corresponding standard deviations. These statistical results highlight the proposed algorithm's accuracy, consistency, and significant improvements. The findings indicate that the IMA outperforms both the QTO and MA approaches, demonstrating superior accuracy, consistency, and enhanced exploration and exploitation capabilities.

Table 4. Definition of terms

Function
$f_1(x) = \sum_{i=1}^{D}(x_i + 0.5)^2$
$f_2(x) = \sum_{i=1}^{n} ix_i^4 + rand(0,1)$
$f_3(x) = \sum_{i=1}^{n}[x_i^2 - 10\cos(2\pi x_i) + 10]$
$f_4(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$
$f_5(x) = \left(\frac{1}{500} + \sum_{j=1}^{25}\frac{1}{j + \sum_{i=1}^{2}(x_i - a_{ij})^6}\right)^{-1}$
$f_6(x) = -\sum_{i=1}^{10}[(X - a_i)(X - a_i)^T + c_i]^{-1}$

Table 5. Benchmarking scenarios of the algorithms

Statistical Parameter		Algorithm		
		QTO [29]	MA	IMA
f_1	Best	0.00E+00	2.37E-18	3.33E-31
	Std.	4.29E+03	3.37E+01	6.02E-01
	Mean	8.48E+00	1.08E+01	1.20E-01
f_2	Best	3.51E-03	4.16E-04	5.14E-04
	Std.	5.84E+00	3.15E-04	1.91E-04
	Mean	6.10E-03	5.43E-04	5.66E-04
f_3	Best	0.00E+00	9.95E-01	9.95E-01
	Std.	9.97E+01	3.82E-01	5.26E-01
	Mean	0.00E+00	1.07E+00	1.22E+00
f_4	Best	0.00E+00	0.00E+00	0.00E+00
	Std.	2.93E+01	5.42E-07	5.21E-04
	Mean	1.52E-02	7.78E-08	8.08E-05
f_5	Best	9.98E-01	9.98E-01	9.98E-01
	Std.	2.90E+00	3.60E-02	3.63E-02
	Mean	6.05E+00	1.00E+00	1.00E+00
f_6	Best	-1.05E+01	-1.05E+01	-1.05E+01
	Std.	2.75E+00	1.63E+00	1.75E+00
	Mean	-3.04E+00	-1.02E+01	-1.01E+01

4.3 Economic dispatch optimization

The first case study focuses on optimizing ED for the mid-day peak load, which totals 774.8 MW. The optimization result for the mid-day peak load is illustrated in the generation cost convergence graph in Figure 1 and summarized in Table 6, showing results over 100 iterations. The QTO method converges by the 41st iteration with a generation cost of Rp. 521.142.678,34per hour, achieving a 24.24% reduction. The MA method converges by the 20th iteration with a generation cost of Rp. 521.131.360,88 per hour, resulting in a 24.25% reduction. The IMA method, proposed in this study, converges most quickly by the 13th iteration, achieving the lowest generation cost of Rp. 520.900.804,14 per hour, reflecting a 24.28% reduction. The total power allocated to the thermal power plant is 657.101 MW using QTO (a reduction of 6.7544%), 657.099 MW using MA (a reducing of 6.7547%), and 657.099 MW with IMA (a reduction of 6.7547%). In terms of RESs, the total generation capacity using the QTO method is 162.55 MW, marking a 38.10% increase from initial values. The MA method results in a total generation of 162.783 MW, reflecting a 38.31% increase, while the IMA method achieves the highest total generation capacity of 162.653 MW, representing a 38.19% increase from previous levels. Under real conditions, the losses are 47.603 MW. After optimization, the losses are reduced as follows: with the QTO method, losses decrease to 44.854 MW, reflecting an 5.77% reduction; with the MA method, losses decrease to

45.084 MW, representing a 5.29% reduction; and with the proposed IMA method, losses decrease to 44.950 MW, indicating a 5.57% reduction.

The second case study focuses on the nighttime peak load, with a total system load of 842.6 MW. The optimization result for the nighttime peak load is illustrated in the generation cost convergence graph in Figure 2 and summarized in Table 7. The QTO method achieves computational convergence at the 39th iteration, with a generation cost of Rp. 601.091.857,75 per hour, representing a 25.96% reduction. The MA method converges at the 13th iteration, with a generation cost of Rp.598.460.148,02 per hour, resulting in a 26.28% reduction. The proposed IMA method demonstrates the fastest convergence, reaching the optimal solution by the 12th iteration with the lowest generation cost of Rp. 594.879.554,43 per hour, reflecting a 26.72% reduction. The total power allocated to the thermal power plant is 739.329 MW using QTO and MA (a reduction of 6.4022%), and 739.331 MW with IMA (a reduction of 6.4018%). The total generation from RESs using the QTO method is 148.95 MW, representing a 44.231% increase from the initial values. The MA method results in a total generation of 148.321 MW, reflecting a 43.62% increase, while the proposed IMA method yields a total generation of 146.951 MW, marking a 42.29% increase. The losses are as follows: using QTO, 45.679 MW (a reduction of 9.67%); using MA, 45.051 MW (a reduction of 10.92%); and using the proposed IMA method, 43.684 MW (a reduction of 13.62%). The IMA method achieves the most significant reduction in losses, with a decrease of 13.62%. Additionally, the lowest generation cost is attained with the proposed IMA-based method.

4.4 Discussion

The algorithmic process for identifying the optimal solution is illustrated by the convergence curves in Figure 1-2. These curves highlight the performance and effectiveness of each algorithm in achieving the optimal solution. The results clearly indicate that the IMA outperforms both the QTA and the standard MA in terms of convergence. Based on the statistical tests conducted, the choice between QTA and IMA ultimately depends on the specific application and problem context.

Tabel 6. Comparison of generation cost optimization results for mid-day peak loads

No Bus	QTO		MA		IMA	
	P (MW)	Cost (Rp/hr)	P (MW)	Cost (Rp/hr)	P (MW)	Cost (Rp/hr)
3	1	1.196.899,55	1	1.196.899,55	0.986224184	1.175.936,117
4	40.13549823	23.910.261,33	38.67175695	22.776.782,58	38.9999996	23.028.860,614
6	200	140.118.609,20	200	140.118.609,20	200	140.118.609,200
7	200	144.367.551,33	200	144.367.551,33	200	144.367.551,325
8	2.767023394	3.899.458,59	4.239144464	5.025.808,37	3.309058196	4.312.743,819
9	1.00	1.511.782,50	1	1.511.782,50	0.80	1.438.868,800
12	200	199.244.375,00	200	199.244.375,00	200	199.244.375,000
13	10	4.828.640,00	10	4.828.640,00	10	4.828.640,000
15	1	2.065.100,83	2.188098581	2.060.912,35	2.999999987	2.385.219,268
Total	**657.101**	**521.142.678,34**	**657.099**	**521.131.360,88**	**657.099**	520.900.804,14
%	**6.7544**	**24.24**	**6.7547**	**24.25**	**6.7547**	**24.28**

Tabel 7. Comparison of generation cost optimization results for nighttime peak loads

No Bus	QTO		MA		IMA	
	P (MW)	Cost (Rp/hr)	P (MW)	Cost (Rp/hr)	P (MW)	Cost (Rp/hr)
3	1	1.196.899,55	1	1.196.899,55	2.421608104	4.056.977,424
4	50	32.179.723,50	50	32.179.723,50	50	32.179.723,500
6	200	140.118.609,20	200	140.118.609,20	200	140.118.609,200
7	200	144.367.551,33	200	144.367.551,33	200	144.367.551,325
8	77.22900003	76.359.677,86	73.90738187	72.453.975,36	65.1416059	62.448.733,764
9	1	1.511.782,50	1	1.511.782,50	1	1.511.782,500
12	200	199.244.375,00	200	199.244.375,00	200	199.244.375,000
13	10	4.828.640,00	10	4.828.640,00	9.990366324	4.822.367,283
15	0.1	1.284.598,81	3.421618132	2.558.591,58	10.77815173	6.129.434,434
Total	**739.329**	**601.091.857,75**	**739.329**	**598.460.148,02**	**739.331**	**594.879.554,43**
%	**6.4022**	**25.96**	**6.4022**	**26.28**	**6.4018**	**26.72**

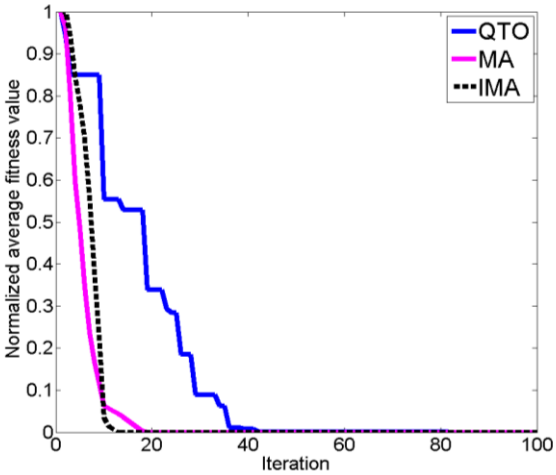

Figure. 1 Convergence graph for mid-day peak load

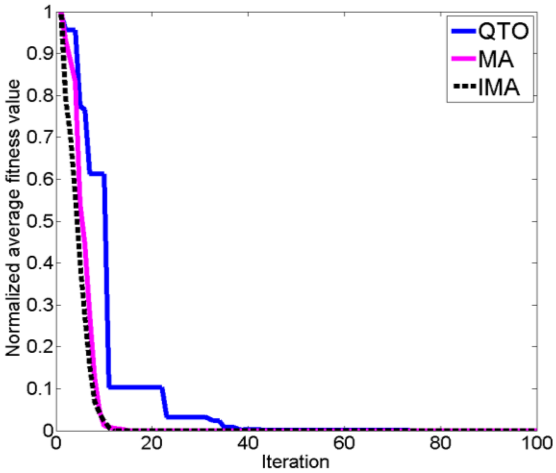

Figure. 2 Convergence grap for nighttime peak load

Table 8. Comparison by application

Feature	QTO	IMA
Scalability	Poor for large datasets	Excellent for large-scale problems
Convergence Speed	Slow, exhaustive	Fast with proper tuning
Accuracy	Exact for small problems	High, though sometimes approximate
Adaptability	Static, lacks flexibility	Adaptive to dynamic problems
Ease of Implementation	Simple	Moderate to complex
Use Case Examples	Small-scale optimization, brute force	Multi-modal, nonlinear problems

Table 8 provides a detailed comparison of the two approaches to assist in selecting the most suitable method for the given problem. QTO refers to addressing problems where time complexity is a significant factor, often arising in brute-force or exhaustive search approaches. It is not a specific algorithm but rather a category of computational effort. In contrast, the IMA is a swarm intelligence-based optimization algorithm inspired by the mating behavior of mayflies. It effectively combines exploration and exploitation aspects to solve complex optimization problems efficiently.

5. Conclusion

The improvement of swarm intelligence performance in this study is achieved through the use of the improved mayfly algorithm (IMA) with the exponent decreasing inertia weight (EDIW) strategy. The IMA's exploration, exploitation, local optima avoidance, and convergence characteristics are evaluated using six benchmark functions. Results indicate that the IMA is highly competitive compared to other intelligence methods, such as the quadratic time optimization (QTO) and standard MA. Specifically, the IMA demonstrates superior performance in both exploration and exploitation tasks, effectively avoiding local optima and achieving efficient convergence, making it a robust choice for optimization challenges. Notably, the IMA excels on fixed-dimension multimodal benchmark functions, showcasing its strength in exploiting unimodal functions, exploring multimodal functions, and handling low-dimensional optimization problems effectively.

The IMA achieves optimal results in maximizing ED for the Sulbagsel system with renewable energy sources (RESs) across both mid-day and nighttime peak loads. The optimization results indicate that, for mid-day peak loads, the QTO approach reduces thermal generation costs by 24.24%, the MA method by 24.25%, and the proposed IMA-based method achieves the largest decrease at 24.28%. Regarding losses, the IMA approach yields a reduction of 5.57%, while QTO and MA achieve reductions of 5.77% and 5.29%, respectively. For nighttime peak loads, thermal generation costs decrease by 25.96% using QTO, 26.28% with MA, and 26.72% with the proposed IMA method. Additionally, losses are reduced by 9.67% with QTO, 10.92% with MA, and 13.62% with the proposed IMA method.

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Notation List

Parameters	Notation
$\boldsymbol{F_T}$	Fuel consumption (Rp/hr),
$\boldsymbol{P_T}$	Output power of the generators (MW)
$\boldsymbol{P_R}$	Load (MW)
H_n	Fuel input of the generator (L/hr)
α_n, β_n, γ_n	Input-output constants of generator.
P_L	Transmission losses (MW).
B_{ij}	Loss coefficients
B_{i0}, B_{00}	Constants related to the losses.
Itr	Iteration
G	Weight of inertia
a_1	Ratio of inertia for damping weight
a_2; a_3	Coefficient of global learning
β	Sight coefficient for distance
f1	Random flight
fl_damp	Parameters for mating
nc	Total offspring count
mu	Total mutant count

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Author Contributions

Conceptualization, IR, RNH; Methodology, MRD, HLG; Software, VL, WH, MAP; Validation, MRD, S; Formal Analysis, IR, HLG; Investigation, WH, MRD; Resources: MAP, VL, S; Writing Original Draft Preparation, WH; Writing Review and Editing, MRD; Visualization, MAP.

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