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Economic Dispatch of Thermal Generators via Bio-Inspired Optimization Techniques

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Abstract This paper addresses the economic dispatch problem in thermal power systems using four metaheuristic optimization algorithms: Particle Swarm Optimization (PSO), Crow Search Algorithm (CSA), Salp Swarm Algorithm (SSA), and JAYA algorithm. A deterministic formulation is adopted to minimize the total generation cost over a 24-hour horizon while meeting generator operating constraints and ensuring load balance. A randomly generated dispatch strategy is also included as a baseline. Each algorithm is independently executed 100 times to evaluate robustness, repeatability, and associated CO_2 emissions. Among all methods, PSO achieves the best performance, yielding the lowest total dispatch cost of \$82,412.78 and the smallest relative standard deviation (0.12%), along with total CO_2 emissions of 1901.65 kg. Compared to other techniques, PSO provides cost improvements of 0.20% over CSA, 0.28% over SSA, 0.94% over JAYA, and a substantial 29.23% reduction with respect to the random baseline. Moreover, all metaheuristic strategies significantly outperform the random dispatch, demonstrating their ability to generate high-quality and feasible solutions. The PSO-based dispatch strategy efficiently allocates hourly power outputs within technical constraints, introducing a controlled overgeneration margin to compensate for system losses. These results confirm the effectiveness of metaheuristic approaches in complex power system optimization tasks and establish a foundation for future work involving renewable integration, emission constraints, and uncertainty modeling.

Keywords Economic dispatch, Metaheuristic optimization, Thermal generators, CO_2 emissions, Single-bus test system

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1. Introduction

The accelerated growth of the global population has led to a substantial increase in the demand for essential resources, among which electrical energy stands out due to its pivotal role in the economic, social, and technological development of nations [1]. Ensuring a reliable, secure, and continuous energy supply necessitates the design and operation of robust power systems capable of adapting to the dynamic variations of their environment [2]. In this context, renewable energy sources have gained considerable importance over the past decades. However, the effective integration of these sources into electric power systems presents significant challenges due to their intermittent nature and vulnerability to geopolitical, economic, and climatic factors [3]. Consequently, two-thirds of the global increase in energy demand is still being met through fossil fuels, particularly in non-interconnected zones or regions with geographical and economic constraints [4].

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In this context, the deployment of thermal generators has become a widely adopted solution to ensure basic energy supply. However, this approach entails high operational costs, significant exposure to fossil fuel market volatility, and considerable contributions to greenhouse gas emissions [5]. In response to these challenges, the economic dispatch of thermal generators remains a fundamental strategy for enhancing the operational efficiency of power systems. It enables the optimal allocation of generation resources with the objective of minimizing total production costs, while complying with the system's technical and operational constraints [6]. This process is conducted over defined time horizons and accounts for demand variability as well as the technical capabilities of generating units, including generation limits, ramp rate constraints, and nodal power balance requirements[7].

It is essential to emphasize that the primary objective of economic dispatch is to minimize the total generation cost of electrical energy in power systems. Therefore, the determination of appropriate generation levels for each thermal unit must be based on rigorous mathematical models and grounded in optimization theory.

1.1. Related literature

Over the past decades, a considerable body of research has been dedicated to the economic dispatch problem, particularly in the context of thermal power generation. Early approaches were grounded in classical optimization methods such as linear programming [8], quadratic programming [9], and gradient projection methods [10], which enabled the formulation of cost minimization models under simplified operating constraints . However, the non-convex nature of real-world economic dispatch problems—arising from valve-point effects, prohibited operating zones, and ramp-rate limits—prompted the development of more sophisticated solution strategies.

To address these complexities, various metaheuristic and evolutionary algorithms have been proposed, including Genetic Algorithms [11] , Particle Swarm Optimization [12], Multi Objetive Algrorithms [13], and more recently, hybrid approaches that combine the strengths of multiple techniques [14]. These methods have demonstrated significant improvements in terms of convergence speed, solution quality, and robustness under uncertain and dynamic operating conditions.

In the study developed by [15], an economic dispatch model for active distribution networks is proposed, incorporating the admissible net load region. The model employs an affine adjustable optimization formulation, enabling the system to adapt to real-world load disturbances. The proposed objectives were to minimize total system costs and maximize the admissible region. These were validated under different test scenarios, yielding acceptable results by reducing total system costs by 3.03% while maintaining 98.46% of the admissible load region under load disturbances of up to 40%. Meanwhile, [16] addresses the economic dispatch problem in microgrids, focusing on the joint optimization of generation and storage resources over multiple time horizons. The methodology is based on a variable neighborhood search algorithm with a dynamic window, adaptive to the solution space. The model was validated using real-world data measured over a one-year period (8760 hours) at the School of Control Science and Engineering of Shandong University in Jinan, China, demonstrating its applicability and efficiency in diverse operational environments, achieving a 23.58% reduction in total system costs and a 33.95% decrease in carbon emissions.

In [17], a bilateral economic dispatch model is proposed, aimed at simultaneously optimizing system stability and operational costs, specifically for wind-based power systems. An iterative classification-based optimization method is employed, considering the variability in supply and demand. The validation was conducted on the IEEE 39-bus test system, and the results indicated that the implemented strategy enhanced system stability while maintaining operational costs with variations below 0.6%. Another approach, presented in [18], addresses stochastic economic dispatch in combined heat and power (CHP) systems using renewable energy sources. The model integrates stochastic optimization techniques with real data on generation and demand variability. The objective was to minimize operational costs over a 24-hour period across multiple scenarios generated using Generative Adversarial Networks (GANs). The results showed a daily cost reduction of up to 2.5% for all test scenarios including renewable sources.

On the other hand, in [19], the authors examine the economic dispatch problem in modern power systems incorporating the dynamic load flow of electric vehicles. The proposed methodology is based on a metaheuristic algorithm called Regional Dual-population Heap-Based Optimization, validated under four electric vehicle charging scenarios. These scenarios are modeled using probabilistic distributions of charging behavior at different times of the day. The results show that the algorithm achieved a generation cost of 1,057,920.7 USD in a scenario with ten generation units and transmission losses, representing an improvement in economic efficiency under varying hourly load profiles. Similarly, in [20], a model is introduced that integrates economic dispatch with sustainability and efficiency criteria in systems equipped with FACTS devices. The objective is to simultaneously minimize operational costs, transmission losses, and emissions. The model is solved using the Arithmetic Optimization Algorithm and tested on IEEE 30-, 57-, and 118-bus systems, showing significant improvements in all cases. Specifically, the system losses were reduced from 3.1129 MW to 2.8469 MW for the 30-bus system, from 11.366 MW to 10.0656 MW for the 57-bus system, and from 73.2977 MW to 64.2368 MW for the 118-bus system.

Finally, [21] addresses the economic dispatch problem of thermal generators without accounting for system losses, while [22] extends the model to include the effects of energy dissipation and transmission losses. In a more comprehensive approach, [23] proposes a realistic formulation that integrates detailed characteristics of the electrical network, such as line impedances, maximum transmission capacities, and both active and reactive power flows, thereby broadening the technical scope of the economic dispatch problem.

1.2. Research focus and contribution

Although numerous studies have addressed the economic dispatch problem in modern power systems based on renewable energy sources—seeking to optimize their technical and operational performance—many energy infrastructures continue to rely heavily on fossil fuel-based generation. These conventional systems face significant challenges that compromise their efficiency and long-term sustainability, primarily due to high operational costs and adverse environmental impacts.

In light of this situation, the development of intelligent strategies for managing the economic dispatch of thermal generators has become imperative. These strategies must not only minimize operational expenditures but also mitigate CO_2 emissions associated with electricity generation, thereby improving the efficiency and economic viability of energy supply systems dependent on conventional technologies.

In response, this article proposes an optimization strategy aimed at enhancing the economic dispatch of thermal generation units. The main objective is to minimize both operational costs and CO_2 emissions. The study is grounded in a classical economic dispatch formulation that explicitly incorporates electrical losses and is applied to a test system comprising three thermal generators supplying a single-node distribution network.

The proposed strategy is implemented through a comparative analysis of five metaheuristic algorithms: Particle Swarm Optimization (PSO), Crow Search Algorithm (CSA), Salp Swarm Algorithm (SSA), and JAYA. These algorithms are evaluated based on solution repeatability and average performance across multiple simulation runs.

Additionally, the model integrates demand variability across a 24-hour time horizon, thereby offering a more realistic and representative analytical framework that captures the dynamic behavior of modern power systems.

The use of bio-inspired metaheuristics in thermal economic dispatch is particularly advantageous due to the inherent non-linearity, non-convexity, and multimodality of the problem, which arises from generator operational constraints. Unlike classical gradient-based or deterministic approaches that may get trapped in local minima or require convex formulations, bio-inspired algorithms such as PSO, CSA, SSA, and JAYA exhibit strong global search capabilities, flexibility in handling complex constraint landscapes, and robustness to non-differentiable objective functions. Moreover, their population-based nature allows for effective exploration of high-dimensional solution spaces (e.g., 72 decision variables in our test case), making them especially suitable for real-world thermal dispatch problems characterized by high dimensionality and multiple local optima. The main contributions of this article are as follows:

- Incorporation of environmental impact considerations into the optimization process through the mathematical formulation of the economic dispatch problem for thermal generators.
- Adaptation of five metaheuristic optimization strategies to solve the economic dispatch problem in thermal generation systems, specifically Particle Swarm Optimization, Crow Search Algorithm, Salp Swarm Algorithm, and JAYA.

- Identification of the Particle Swarm Optimization algorithm as the most suitable technique for managing the economic dispatch of thermal generators in power systems, based on a statistical analysis of solution quality and repeatability.

1.3. Organization

The remainder of this article is organized into five sections. Section 2 presents the mathematical formulation of the economic dispatch problem for thermal generators, including CO_2 emissions. Section 3 describes the methodology, detailing the fitness function, encoding scheme, and the metaheuristic optimization techniques employed. Section 4 outlines the test system used to validate the proposed approach. Section 5 provides a statistical analysis of the obtained results. Finally, Section 6 presents the main conclusions of the study.

2. Mathematical model

The economic dispatch of generation units is a fundamental problem in the operation of power systems. Its primary objective is to determine the optimal generation allocation for each unit in order to meet the electrical demand at the lowest possible cost. Consequently, it is essential to formulate a mathematical model that accurately represents the system's behavior within a technical, economic, and environmental context. To this end, the objective function and the corresponding set of technical constraints are defined as follows.

2.1. Objective function

In this study, the objective function corresponds to the minimization of the total production cost associated with all thermal generating units in the power system. Accordingly, the generation costs are modeled using the quadratic cost function presented in Equation (1).

$$\min C(PG) = \sum_{k\in G}\sum_{h\in H}\left(a_k \cdot {PG_{k,h}}^2 + b_k \cdot PG_{k,h} + c_k\right) \tag{1}$$

where C represents the total operational cost of the system, $PG_{k,h}$ is the power injected by the k-th thermal generator during period h, a_k and b_k are the variable cost coefficients of the k-th generating unit, c_k denotes the fixed cost, G is the set of generators considered, and H is the set of time periods.

Based on the cost minimization objective function, it is also possible to define Equation (2), which determines the CO2 emissions associated with the minimum-cost generation scheme.

$$E(PG) = \sum_{k\in G}\sum_{h\in H}\left(\mathrm{FE}_k \cdot PG_{k,h}\right), \quad \forall k \in G, \forall h \in H \tag{2}$$

where E represents the total amount of CO_2 emissions released into the atmosphere during one day of continuous operation, and FE_k denotes the emission factor associated with the k-th thermal generator.

2.2. Set of Constraints

Given the nature of the problem addressed in this study, which considers a single-node electrical network, the first constraint corresponds to the active power balance between generation and demand. Ideally, this is represented by Equation (3).

$$\sum_{k\in G} PG_{k,h} \geq \sum_{j\in D} PD_{j,h}, \quad \forall j \in D,\ \forall h \in H \tag{3}$$

where $PD_{j,h}$ represents the power consumed by the j-th demand during hour h, and D denotes the set of loads in the power system.

To more accurately represent the real operation of thermal generators, it is possible to incorporate the effect of active power losses into the model through a quadratic approximation of the generated powers, as described in Equation (4). This representation preserves the simplicity of the original model while improving its realism and enabling a more precise allocation of generation resources.

$$PL_h = \sum_{k \in G} \sum_{m \in G} B_{k,m} \cdot PG_{k,h} \cdot PG_{m,h}, \quad \forall h \in H \tag{4}$$

where PL_h represents the active power losses during hour h, and $B_{k,m}$ is a coefficient that denotes the contribution of each generator pair, i.e., it corresponds to the loss coefficient between generators k and m. It is worth noting that when $k = m$, the expression yields a quadratic loss component associated with the active power generation of the k-th thermal unit.

Thus, by combining Equations (3) and (4), it is possible to derive a single constraint that represents the active power balance, as expressed in Equation (5).

$$\sum_{k \in G} PG_{k,h} \geq \sum_{j \in D} PD_{j,h} + \sum_{k \in G} \sum_{m \in G} B_{k,m} \cdot PG_{k,h} \cdot PG_{m,h}, \quad \forall h \in H \tag{5}$$

Finally, Equation (6) defines the minimum and maximum power capacity limits for each thermal generator.

$$PG_k{}^{\min} \leq PG_{k,h} \leq PG_k{}^{\max}, \quad \forall k \in G, \forall h \in H \tag{6}$$

where $PG_k{}^{\min}$ and $PG_k{}^{\max}$ represent the minimum and maximum power capacities, respectively, associated with the k-th thermal generator. This equation ensures that the operating conditions of each thermal generation unit remain within their operational limits during every hour of the scheduling horizon.

3. Methodology

Given the metaheuristic approach adopted in this study, it is first necessary to establish a set of methodological arrangements that allow the proposed algorithms to explore the search space through both feasible and infeasible regions of the problem. For this reason, this research defines a fitness function (ff) and an encoding scheme, which jointly guide each of the proposed optimization algorithms in solving the mathematical model presented in Section 2.

3.1. Fitness function

This methodology incorporates a set of penalty terms into the objective function to enable each optimization algorithm to guide its evolutionary process toward regions of the search space that represent technically feasible solutions and economically efficient outcomes. Equation (7) presents a fitness function tailored to the mathematical formulation of the economic dispatch problem.

$$ff = C + Pen \tag{7}$$

where C represents the value of the objective function described in Equation (1), and Pen is a penalty term constructed based on the technical constraints of the problem.

The purpose of the penalty factor is to allow the optimization algorithms to explore the solution space even when violations of Equation (5) occur. In other words, the penalty term penalizes infeasible solutions by increasing their objective value. The penalty factor is computed using Equation (8).

$$Pen = \begin{cases} \sum_{h \in H} \beta + |\beta \cdot (PG_h - (PD_h + PL_h + +))|, & \text{if} \quad PG_h < PD_h + PL_h \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

where PG_h represents the total power generated by all generators in the system during hour h, PD_h is the total demand during hour h, PL_h corresponds to the power losses during hour h, and β is a penalty factor heuristically adjusted according to the problem conditions.

It should be noted that the penalty term is always positive in the presence of a generation deficit, due to the use of the absolute value in the equation. In this study, the penalty factor was set to $\beta = 100$.

3.2. *Codification*

To represent the economic dispatch problem, a vector-based encoding of dimensions $[1, H \times G]$ is defined, allowing each candidate solution to be represented within the solution space explored by the different optimization algorithms. In this vector representation, H denotes the number of time periods considered; in this study, 24 time intervals corresponding to one full day of operation are analyzed. On the other hand, G represents the number of thermal generators considered in the power system. In this specific case, three thermal generation units are included.

As illustrated in Figure 1, each position in the encoding vector corresponds to the amount of power to be dispatched at each time period for each generator. It is important to note that these power values are bounded by the technical constraints of each generator, namely, the minimum and maximum capacity limits defined by the nominal ratings of the thermal units.

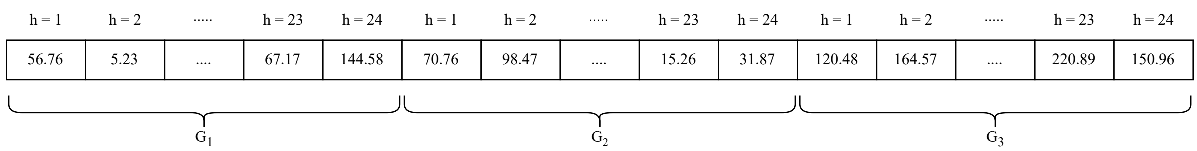

Figure 1. Hourly dispatch encoding of thermal generators

It is important to highlight that the problem addressed is classified as NP-hard, which implies that it is not possible to find an exact solution in non-polynomial time. This is due to the fact that the number of variables increases with the number of generators in the system. Additionally, the solution space is continuous within the operational limits of the generators, thus categorizing the problem as combinatorial in nature. Specifically, in the case of three generators, the problem involves 72 decision variables, each of which can take any value within the operating range of its respective generator. This results in a continuous optimization problem where the application of classical mathematical optimization techniques is not suitable.

3.3. *Optimization Process*

The resolution of the Economic Dispatch Problem in this study is based on the application of metaheuristic algorithms that iteratively explore the search space to identify optimal or near-optimal solutions.

In this article, four metaheuristic optimization techniques are employed to address the Economic Dispatch Problem. All of them are population-based algorithms: the Crow Search Algorithm, the JAYA Algorithm, the Particle Swarm Optimization algorithm, and the Salp Swarm Algorithm.

It is worth noting that, in population-based optimization algorithms, the search process begins with an initial population matrix denoted as $\mathbf{X}$, which defines the solution space associated with the optimization problem. During each iteration, the individuals within this population update their positions according to specific motion rules defined by each algorithm. Equation (9) shows the general structure of the initial population matrix.

$$\mathbf{X}^t = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,j} & \cdots & x_{1,n_v} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,j} & \cdots & x_{2,n_v} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{k,1} & x_{k,2} & \cdots & x_{k,j} & \cdots & x_{k,n_v} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n_s,1} & x_{n_s,2} & \cdots & x_{n_s,j} & \cdots & x_{n_s,n_v} \end{bmatrix} \quad (9)$$

It is important to highlight that the matrix of individuals $\mathbf{X}^t$ has dimensions $n_s \times n_v$, where n_s denotes the total number of individuals defined in the optimization process, and n_v corresponds to the number of decision variables of the problem. The superscript t refers to the current iteration number. Each element $x_{k,j}$ represents the value assigned to the j-th variable of the k-th individual, which must lie within the lower and upper bounds established for that variable. In this particular study, each variable must satisfy the operational limits specified in Equation (6). To ensure a proper initialization of the individuals matrix from the first iteration ($t = 0$), Equation (10) is employed.

$$x_{k,j}^0 = x_j^{\min} + \alpha_j \left(x_j^{\max} - x_j^{\min} \right), \quad \forall j = 1, 2, \ldots, n_v, \ \forall k = 1, 2, \ldots, n_s \quad (10)$$

where $x_j^{\min}$ and $x_j^{\max}$ represent the minimum and maximum values allowed for the j-th decision variable, respectively, and α_j is a random number uniformly distributed in the interval $[0, 1]$. In the context of economic dispatch, each individual in the numerical array represents the power output assigned to thermal generating units throughout the scheduling horizon.

3.3.1. Crow Search Algorithm: this metaheuristic optimization technique is designed to address problems of various types, including continuous, integer, and binary formulations. It exhibits a well-balanced trade-off between exploration (diversification) and exploitation (intensification), and it is capable of performing both local and global searches effectively. The algorithm's underlying philosophy is inspired by the natural behavior of crows: these birds store surplus food in hidden locations and return to retrieve it when needed. Furthermore, it is assumed that a crow may follow another in an attempt to locate its hiding place and steal the cached food [24].

The evolutionary process of the algorithm is guided by the following parameters:

- The flight length of each crow, denoted as fl, which must take values strictly greater than zero.
- The awareness probability AP, which is defined in the range $[0, 1]$.

Additionally, the algorithm utilizes a memory structure M, which has the same dimensions as the population matrix X and is initialized following equation (10). Once both the initial population and the memory for each individual are defined, the fitness function is evaluated according to equation (7), and the iterative cycle begins.

At this stage, there are two possible update strategies for each individual in the population, as defined by the conditional rule in equation (11):

$$x_k^{t+1} = \begin{cases} x_k^t + r_i \cdot fl_k^t \cdot \left(m_j^t - x_k^t \right), & \text{if } r_j \geq AP_i^t \\ \text{A random position within the search space,} & \text{otherwise} \end{cases} \quad \forall k = 1, 2, \ldots, N_s. \quad (11)$$

where r_i and r_j are random numbers uniformly distributed in the interval $[0, 1]$, and fl_k^t denotes the flight length of crow k in iteration t.

The progression of the algorithm toward promising regions (i.e., higher-quality solutions) is reinforced through a memory mechanism, where the best individuals are stored in the matrix m. In this context, a candidate solution x_k^{t+1} is stored in the memory m_j^{t+1} only if its fitness is superior to that of the previously stored solution m_j^t, as defined in Equation (12):

$$m_j^{t+1} = \begin{cases} x_k^{t+1}, & \text{if } ff(x_k^{t+1}) < ff(m_j^t) \\ m_j^t, & \text{otherwise} \end{cases} \quad (12)$$

The evolutionary process of the Crow Search Algorithm (CSA), as adapted to the Economic Dispatch Problem of thermal generators, is formally summarized in Algorithm 1.

Algorithm 1: Crow Search Optimization Algorithm

Data: Read the input parameters of the optimization problem

Define the lower and upper bounds of the decision variables for each generator, i.e., $x^{\min}$ and $x^{\max}$;
Set the values of N_s (number of individuals), N_v (number of variables), $t_{\max}$ (maximum number of iterations), fl (flight length), and AP (awareness probability);
Generate the initial population x^0 and the initial memory m^0 according to Equations (9) and (10);
Evaluate the fitness function for each individual in the population and in the memory using Equation (7);
for $t = 1$ **to** $t_{\max}$ **do**
  for $k = 1$ **to** N_s **do**
    Randomly select a crow to follow, denoted as x_j;
    if $r_j \geq AP$ **then**
      Update the position of individual k according to:
      $x_k^{t+1} = x_k^t + r_k \cdot fl_k^t \cdot (m_j^t - x_k^t)$;
    else
      Assign x_k^{t+1} a random position within the search space;
    if $f(x_k^{t+1}) < f(m_j^t)$ **then**
      Update memory: $m_j^{t+1} = x_k^{t+1}$;
    else
      Retain memory: $m_j^{t+1} = m_j^t$;
Sort the memory matrix m in ascending order of fitness values;

Result: Return the best solution found: $m_1^{t_{\max}}$

3.3.2. JAYA Optimization Algorithm: This population-based optimization algorithm leverages the advancement strategies of bio-inspired evolutionary algorithms to define its search and convergence criteria. Its main strength lies in its ability to achieve high-quality solutions while maintaining low implementation complexity. JAYA employs the "survival of the fittest" principle by guiding the population toward higher-quality regions in the search space. It does so using two sets of individuals: the current population and a corresponding displacement population, which facilitates movement toward the best solution and away from the worst one [25].

Unlike many other optimization algorithms, JAYA does not require algorithm-specific control parameters for its search process. Therefore, both the number of individuals n_s and the maximum number of iterations $t_{\max}$ must be tuned according to the characteristics of the problem to ensure optimal performance.

The algorithm begins by generating the initial population using Equations (9) and (10), followed by the evaluation of each individual using the fitness function defined in Equation (7). This evaluation allows for the identification of the best and worst individuals in the population.

To guide the population toward more promising regions of the solution space, JAYA generates an auxiliary population matrix (y^t), which is responsible for updating the positions of individuals in the current population (x^t) during each iteration t. This update process is driven by the information of the best individual (x_1) and the worst individual (x_{n_s}).

The auxiliary matrix y^t has the same dimensions as the original population matrix, maintaining the same number of individuals and decision variables. The corresponding fitness function is also applied to each new solution.

The advancement and replacement rule for each individual in the population is defined by Equations (13) and (14).

$$y_{k,j}^t = x_{k,j}^t + R_1\left(x_{1,j}^t - |x_{k,j}^t|\right) - R_2\left(x_{n_s,j}^t - |x_{k,j}^t|\right), \quad \{\forall j = 1, 2, \ldots, n_v,\ \forall k = 1, 2, \ldots, n_s\} \tag{13}$$

where R_1 and R_2 are random numbers normally distributed within the range $[0, 1]$. These parameters are essential for promoting solution diversity and preventing premature convergence to local optima.

The decision to replace an individual in the current population with the corresponding candidate in the auxiliary population is governed by the following condition:

$$x_k^{t+1} = \begin{cases} y_k^t & \text{if } ff\left(y_k^t\right) < ff\left(x_k^t\right), \\ x_k^t & \text{otherwise,} \end{cases} \qquad \{\forall k = 1, 2, \ldots, n_s\} \tag{14}$$

Algorithm 2 outlines the iterative process and convergence mechanism of the JAYA optimization method, adapted to solve the economic dispatch problem of thermal generation units.

Algorithm 2: JAYA Optimization Algorithm

Data: Read problem parameters and configuration values

Define the lower and upper bounds of each decision variable, i.e., $x^{\min}$ and $x^{\max}$;
Define the values of n_s (population size), n_v (number of variables), $t_{\max}$ (maximum iterations), and $m_{\max}$ (maximum no-improvement iterations);
Initialize no-improvement counter: $m = 0$;
for $t = 1$ **to** $t_{\max}$ **do**
  if $t = 1$ **then**
    Generate the initial population x^t using equations (9) and (10);
    Evaluate the fitness of each individual in the population $ff(x_k^t)$ using equation (7) for all $k = 1, 2, \ldots, n_s$;
    Sort the population x^t and identify the best solution x_1^t and the worst solution $x_{n_s}^t$;
  if $t \geq 2$ **then**
    Generate the auxiliary matrix y^t using equation (13);
    Evaluate the fitness of each individual in y^t using equation (7);
    Update the population x^t using equation (14);
    Update the best solution x_1^t and the worst solution $x_{n_s}^t$;
  if $ff(x_1^t) \geq ff(x_1^{t-1})$ **then**
    Increment no-improvement counter: $m = m + 1$;
  else
    Reset no-improvement counter: $m = 0$;
  if $m \geq m_{\max}$ **then**
    Report the current best solution x_1^t;
    break;

Result: Report the best solution found, i.e., x_1^t

3.3.3. Particle Swarm Optimization Algorithm: the PSO algorithm mimics the collective foraging behavior of bird flocks and fish schools, relying on two main components to guide the search process: (i) the cognitive component, which represents the individual intelligence of each particle in the swarm (i.e., the ability to recall its own best-known position), and (ii) the social component, which accounts for the shared knowledge of the swarm (i.e., the best-known position found by any particle).

At each iteration, the best solution found so far by the swarm is identified, and this solution becomes the current global leader. The leader may vary over iterations depending on the performance of the particles. Each particle then adjusts its trajectory in the solution space based on both its personal experience and the experience of the global leader, with the aim of converging toward the optimal solution [26].

The algorithm requires the configuration of several parameters: the maximum and minimum values of the inertia weight ($Iner_{\max}$ and $Iner_{\min}$), cognitive and social acceleration coefficients (Φ_1 and Φ_2), and velocity bounds ($Vel_{\max}$ and $Vel_{\min}$).

Additionally, the PSO algorithm employs a velocity matrix that governs the position updates of each particle in the solution space, as defined by Equation (15).

$$\text{Vel}^t = \begin{bmatrix} vel_{1,1} & vel_{1,2} & \cdots & vel_{1,j} & \cdots & vel_{1,n_v} \\ vel_{2,1} & vel_{2,2} & \cdots & vel_{2,j} & \cdots & vel_{2,n_v} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ vel_{k,1} & vel_{k,2} & \cdots & vel_{k,j} & \cdots & vel_{k,n_v} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ vel_{n_s,1} & vel_{n_s,2} & \cdots & vel_{n_s,j} & \cdots & vel_{n_s,n_v} \end{bmatrix}, \tag{15}$$

Each element $vel_{k,j}$ represents the velocity assigned to the j-th decision variable of the k-th particle. This value governs the magnitude and direction of the particle's movement in the solution space and is updated at every iteration according to Equation (16).

$$vel^1_{k,j} = Vel_{min} + \alpha_j \left(Vel_{max} - Vel_{min}\right), \; \{j = 1, 2, ..., n_v, \; k = 1, 2, ..., n_s\} \tag{16}$$

In this way, the first population of individuals is generated using Equation (17), which enables the particles to move across the solution space based on the influence of the velocity matrix.

$$X^t = X^t + \text{Vel}^t, \tag{17}$$

It should be noted that after this update, if any decision variables violate their feasibility bounds, a repair mechanism must be applied. This is done by projecting the infeasible values back into the feasible space using Equation (18):

$$x_{k,j} = \begin{cases} x_j^{\min} & \text{if } x_{k,j} < x_j^{\min} \\ x_j^{\max} & \text{if } x_{k,j} > x_j^{\max} \end{cases}, \quad \{\forall j = 1, 2, \ldots, n_v; \; \forall k = 1, 2, \ldots, n_s\} \tag{18}$$

The population matrix X is evaluated using the fitness function described in Equation (7). Then, each particle identifies its best historical position, denoted as bestpos_i, and stores the corresponding fitness value as fitness_i. Within the swarm, the particle with the best overall fitness is identified, and its position and fitness are saved as the global best position bestpos_g and global fitness fitness_g, respectively.

From the second iteration onward, and until reaching the maximum number of iterations, the PSO algorithm applies the following update rule for the inertia coefficient:

$$\text{Inertia}^t = \text{Iner}_{\max} - \left(\frac{(\text{Iner}_{\max} - \text{Iner}_{\min}) \cdot t}{t_{\max}} \right), \tag{19}$$

In each iteration, the value of the inertia factor Inertia^t is dynamically updated based on the maximum and minimum assigned values ($\text{Iner}_{\max}$ and $\text{Iner}_{\min}$), within a typical range of $[1, 0]$, and as a function of the current iteration t and the total number of iterations $t_{\max}$.

Subsequently, the velocity matrix Vel^t is updated using Equation (20).

$$\text{Vel}^t_{k,j} = \text{Vel}^{t-1}_{k,j} \cdot \text{Inertia}^t + \beta_j \cdot \Phi_1 \cdot (\text{bestpos}_{i_{k,j}} - x^{t-1}_{k,j}) + \gamma_j \cdot \Phi_2 \cdot (\text{bestpos}_{g_{k,j}} - x^{t-1}_{k,j}), \tag{20}$$

where the parameters β_j and γ_j are random numbers uniformly distributed in the range $[0, 1]$, included to enhance solution diversity and reduce the risk of premature convergence to local optima.

Once the velocity matrix is updated, it is necessary to ensure that each velocity component remains within the predefined bounds. This process, known as velocity feasibility, is performed using Equation (21):

$$\text{vel}_{k,j} = \begin{cases} \text{Vel}_{\min}, & \text{if vel}_{k,j} < \text{Vel}_{\min} \\ \text{Vel}_{\max}, & \text{if vel}_{k,j} > \text{Vel}_{\max} \\ \text{vel}_{k,j}, & \text{otherwise} \end{cases}, \quad \forall j = 1, 2, \dots, n_v, \ \forall k = 1, 2, \dots, n_s \tag{21}$$

For each particle, the fitness value of the current iteration is compared to the best fitness previously achieved by the particle, denoted as fitness_i. If the current solution provides an improvement, both the best position bestpos_i and the associated fitness value fitness_i are updated accordingly. This mechanism is formalized in Equation (22).

$$[\text{bestpos}_i, \ \text{fitness}_i] = \begin{cases} [x_i, \ ff(x_i)] & \text{if } ff(x_i) < \text{fitness}_i \\ [\text{bestpos}_i, \ \text{fitness}_i] & \text{otherwise} \end{cases}, \tag{22}$$

Subsequently, following a similar criterion, the best global solution within the swarm is updated using Equation (23):

$$[\text{bestpos}_g, \ \text{fitness}_g] = \begin{cases} [x_i, \ f(x_i)] & \text{if } ff(x_i) < \text{fitness}_g \\ [\text{bestpos}_g, \ \text{fitness}_g] & \text{otherwise} \end{cases}, \tag{23}$$

Algorithm 3 outlines the iterative procedure of the Particle Swarm Optimization, presenting a general overview of its convergence process adapted to the economic dispatch problem of thermal generators.

3.3.4. Salp Swarm Algorithm This algorithm is inspired by the locomotion behavior of salps—marine organisms similar to jellyfish. From an algorithmic perspective, SSA defines two types of movement to explore the solution space and identify high-quality solutions. The first type of movement is governed by the best solution found so far in each iteration, ensuring the updated positions remain within the permissible limits of each decision variable. The second type of movement is based on Newton's second law of motion and requires two neighboring individuals to guide the position update. Each movement includes a stochastic component, which allows the algorithm not only to conduct local searches but also to escape from local optima by exploring new regions of the solution space [27].

The algorithm begins by generating the initial population X and evaluating the fitness function for each individual using Equations (9) and (10), respectively.

The evolutionary process of the SSA is carried out using two distinct update strategies. The first strategy, which applies to the first half of the population, is defined by Equation (24).

$$x^t_{k,j} = \begin{cases} F_j + c_1\left((ub_j - lb_j) \cdot c_2 + lb_j\right) & \text{if } c_3 \geq 0.5 \\ F_j - c_1\left((ub_j - lb_j) \cdot c_2 + lb_j\right) & \text{if } c_3 < 0.5 \end{cases} \begin{cases} \forall j = 1, 2, \dots, n_v \\ \forall k = 1, 2, \dots, n_s/2 \end{cases} \tag{24}$$

In this expression, F_j refers to the position of the food source, which corresponds to the best solution found in the current iteration t. The parameters ub_j and lb_j denote the upper and lower bounds for the j-th decision variable (i.e., $x^{\max}$ and $x^{\min}$ in the context of the economic dispatch problem addressed in this paper). The coefficients c_2 and c_3 are uniformly distributed random numbers in the interval $[0, 1]$, while c_1 is a time-dependent parameter calculated as follows:

Algorithm 3: Particle Swarm Optimization Algorithm

Data: Initialization of the problem-specific parameters

Define the number of decision variables n_v and their lower and upper bounds: $x^{\min}$ and $x^{\max}$;
Set the algorithmic parameters: n_s, $Iner_{max}$, $Iner_{min}$, Φ_1, Φ_2, Vel_{max}, Vel_{min}, t_{max}, and n_{max};
Initialize the stagnation counter $contnm = 0$;
for $t = 1$ **to** t_{max} **do**
  if $t = 1$ **then**
    Generate the initial particle positions x^t using Equation (10);
    Generate the initial velocity matrix Vel^t using Equation (16);
    Update particle positions using Equations (17) and (18);
    Evaluate the fitness function $ff(x_k^t)$ for each particle $k = 1, 2, \ldots, n_s$;
    Identify and store the best personal positions $bestpos_i$ and corresponding fitness $fitness_i$;
    Identify and store the best global position $bestpos_g$ and global fitness $fitness_g$;
  if $t \geq 2$ **then**
    Compute inertia $Inercia^t$ using Equation (19);
    Update velocities Vel^t using Equations (20) and (21);
    Update particle positions X^t using Equations (17) and (18);
    Evaluate the fitness function $ff(x_k^t)$ for each particle $k = 1, 2, \ldots, n_s$;
    Update $bestpos_i$ and $fitness_i$ using Equation (22);
    Update $bestpos_g$ and $fitness_g$ using Equation (23);
  if $f(x_1^t) == f(x_1^{t-1})$ **then**
    Set $contnm = contnm + 1$;
  else
    Set $contnm = 0$;
  if $contnm \geq n_{max}$ **then**
    Return $bestpos_g$ and $fitness_g$ as the final solution;
    break;

Result: Report the best solution found: $bestpos_g$

$$c_1 = 2e^{-\left(\frac{4t}{t_{\max}}\right)^2} \tag{25}$$

Here, t represents the current iteration number and $t_{\max}$ is the maximum number of iterations predefined as a control parameter of the algorithm.

The second update strategy is applied to the remaining half of the population. This rule is based on Newton's Law of Motion and allows for a smoother transition between successive positions. The position update for these individuals is governed by Equation (26):

$$x_j^t = \frac{1}{2}\left(x_j^t + x_{j-1}^t\right), \quad \forall j = \frac{n_s}{2} + 1, \ldots, n_s \tag{26}$$

All salps in the population are sorted from best to worst based on their fitness values. Consequently, the best solution is stored in the first row of the population matrix, X_1^t. This individual is then compared with the current food source vector F_j. If the fitness of X_1^t is better than that of F_j, the food source is updated as $F_j = X_1^t$.

Algorithm 4 presents the iterative procedure of the Salp Swarm Algorithm (SSA), providing a general description of the convergence process tailored to the economic dispatch problem of thermal generators.

Algorithm 4: Salp Swarm Algorithm

Data: Reading the parameters of the problem under analysis

Define the decision variable bounds, i.e., n_v, $x^{\min}$ and $x^{\max}$;
Define the number of individuals n_s and the maximum number of iterations $t_{\max}$;
Generate the initial population X^t randomly using equations (9) and (10);
Evaluate the fitness function for each individual in the population: $ff(x_k^t)\ \forall k = 1, 2, \ldots, n_s$;
Identify and store the best solution found, F_j;
for $t = 1 : t_{\max}$ **do**
    Compute the parameter c_1 using equation (25);
    for $i = 1 : n_s$ **do**
        if $i < n_s/2$ **then**
            Update position of individual i using the first movement rule (equation (24)): $X[i, :] \leftarrow x_i^t$;
        else
            Update position of individual i using the second movement rule (equation (26)): $X[i, :] \leftarrow x_i^t$;
    Evaluate the fitness function for the updated population: $ff(x_i^t)\ \forall i = 1, 2, \ldots, n_s$;
    Update the food source F_j if a better solution is found in X_1^t;

Result: Return the best solution found, i.e., F_j

4. Test System

In order to validate the mathematical model and assess the performance of the four implemented optimization algorithms, a single-node thermal generation system is employed, as illustrated in Figure 2. The system consists of three thermal generators and a predefined hourly demand profile.

This simplified configuration disregards the electrical network behavior; hence, network topology, line impedances, and voltage drops are not considered. The aim is to isolate the economic dispatch problem and focus solely on the optimization of generation costs.

This test system allows the evaluation of the optimization models based on the mathematical formulation introduced in Section 2. The abstraction of network constraints facilitates direct analysis of the algorithms' convergence behavior, solution quality, and the repeatability of the obtained solution.

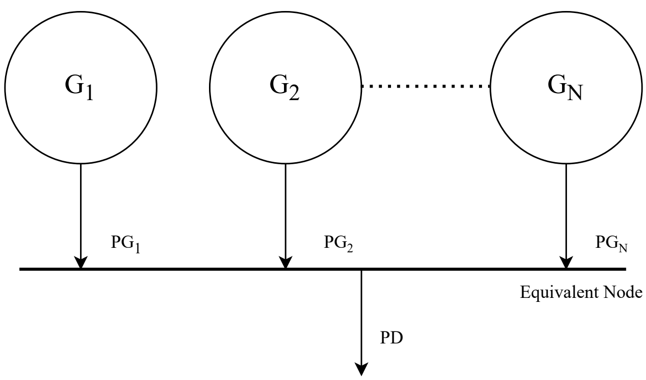

Figure 2. Single-node test system with thermal generators.

The optimization problem addressed in this study is formulated as deterministic; all parameters related to the thermal generation units, the hour-by-hour load demand, and the cost and CO_2 emission factors per kWh generated are assumed to be known. The data corresponding to the test system presented below are reported in [28].

Table 1 presents the cost-related parameters for each thermal generator. These include the coefficients of the variable cost function, denoted by a and b, and the fixed cost coefficient c, which collectively define the fuel cost curve of each unit. Additionally, the table includes the minimum and maximum generation limits of each thermal generator, represented as $P_G^{\min}$ and $P_G^{\max}$, respectively.

Table 1. Cost and operating parameters of the thermal generators

Generator	a [USD/MW^{2}h]	b [USD/MWh]	c [USD]	$P_G^{\min}$ [MW]	$P_G^{\max}$ [MW]
G_1	0.006085	10.04025	136.9125	5	150
G_2	0.005915	9.760576	59.1550	15	100
G_3	0.005250	8.662500	328.1250	50	250

The parameters of the $B_{(k,m)}$ matrix are presented in Table 2. These coefficients represent the transmission losses associated with the interaction between thermal generators in the single-node test system.

Table 2. Loss coefficient matrix $B_{(k,m)}$ among thermal generators

Generators	G_1 [1/MW]	G_2 [1/MW]	G_3 [1/MW]
G_1	0.00013630	0.00006750	0.00007839
G_2	0.00006750	0.00015450	0.00009828
G_3	0.00007839	0.00009828	0.00016140

For this study, the CO_2 emission factors by fuel source reported in Table 3 are used. These values were taken from [29] and converted to units of kg CO_2/kWh. The reported emissions represent only direct emissions resulting from fossil fuel combustion during electricity generation and exclude those related to fuel production and supply processes (e.g., gas transportation, coal mining, or liquefied natural gas (LNG) production).

It is important to note that, for the purpose of this analysis, the assumed generation technologies are Coking coal/bituminous coal for Generator 1, Natural gas for Generator 2, and Gas/diesel oil for Generator 3.

Table 3. CO_2 emission factors by generator type

Generator	Fuel Type	CO_2 Emissions [kg/kWh]
Generator 1	Coking coal/bituminous coal	0.3406
Generator 2	Natural gas	0.2020
Generator 3	Gas/diesel oil	0.2668

Finally, Table 4 presents the discrete hourly load profile used in the simulations, covering a 24-hour time horizon. This demand profile represents the energy requirement at each hour and serves as a key input for evaluating the economic dispatch performance of the optimization algorithms.

While this study considers a test system with three thermal generation units, it is important to note that the computational complexity of the economic dispatch problem increases significantly with the number of generators. As more units are added, the number of decision variables grows proportionally, enlarging the search space and increasing the potential for local optima. In this context, bio-inspired metaheuristic algorithms are particularly advantageous, as they are well-suited for handling high-dimensional, nonlinear, and multimodal optimization problems without requiring gradient information or convexity assumptions.

Table 4. Hourly power demand profile for a 24-hour scheduling horizon

Hour	Demand [MW]	Hour	Demand [MW]	Hour	Demand [MW]	Hour	Demand [MW]
1	210	7	150	13	310	19	450
2	230	8	100	14	320	20	460
3	200	9	80	15	350	21	470
4	180	10	130	16	380	22	420
5	240	11	190	17	400	23	350
6	180	12	280	18	420	24	220

5. Results and Discussion

To address the economic dispatch problem of thermal generators, this study implemented four optimization algorithms as detailed in Section 3. The computational experiments were conducted using MATLAB R2023. All simulations were executed on a personal computer equipped with an Intel(R) Core(TM) i5-1235U processor running at 1.30 GHz, 8 GB of RAM, and a 64-bit Windows 11 operating system.

In this context, each optimization algorithm was independently executed 100 times to evaluate both the effectiveness and robustness of the proposed strategies. The performance assessment focused on key statistical indicators, including the best solution, worst solution, average solution, standard deviation, and total CO_2 emissions. This comprehensive evaluation framework not only provides insights into the quality of the solutions obtained, but also highlights the stability and consistency of each metaheuristic under identical simulation conditions.

Complementarily, the tuning of algorithm-specific parameters is a critical step in the implementation of metaheuristic optimization techniques, as it directly influences their convergence, solution quality, and robustness. In this study, the parameter configuration for each algorithm was determined heuristically, based on preliminary sensitivity analyses and references from recent literature [30]. Table 5 summarizes the main parameters employed for each optimization algorithm used in solving the economic dispatch problem.

In addition to the metaheuristic strategies, a baseline scenario was established to serve as a point of comparison. This case consists of a randomly generated dispatch solution constructed using Equation (10), without any optimization criterion. The inclusion of this baseline allows for a clearer quantification of the improvements achieved through the implementation of intelligent optimization methods.

Table 6 summarizes the statistical performance of the four optimization algorithms implemented to solve the deterministic economic dispatch problem. In addition to the metaheuristic approaches, the table includes the results of a baseline case, providing reference values for both operating cost and CO_2 emissions. This inclusion allows for a clearer comparison of the benefits achieved through optimization.

The results presented in Table 6 provide a comparative assessment of four metaheuristic optimization algorithms, alongside a randomly generated baseline solution, for solving the economic dispatch problem of thermal power generators over a 24-hour operational horizon.

Among the evaluated algorithms, Particle Swarm Optimization demonstrated the best overall performance. It yielded the lowest total cost associated with the economic dispatch of thermal generators, achieving a best-case value of $82,412.7817. In addition, it exhibited the highest solution consistency, with a relative standard deviation of just 0.1247%, indicating robust and repeatable performance.

The CSA and SSA algorithms achieved intermediate results, with average costs of $83,170.4159 and $83,046.7009, respectively. While CSA showed higher variability (0.4194%), SSA offered slightly better repeatability (0.3123%). On the other hand, the JAYA algorithm resulted in the highest average dispatch cost ($83,742.7965) and the largest standard deviation (0.4241%), despite producing one of the lowest CO_2 emission levels (1,899.7974 kg CO_2).

In contrast, the random dispatch strategy exhibited an unacceptably high total cost of $116,440.0000 and the highest emissions (1,929.7846 kg CO_2), confirming the need for intelligent and structured optimization approaches.

Table 5. Heuristically tuned parameters for each optimization algorithm

Algorithm	Parameter	Value
PSO	Population size (n_s)	10000
	Max iterations (t_{max})	20000
	Max inertia ($Inert_{\text{max}}$)	1.000
	Min inertia ($Inert_{\text{min}}$)	1.000
	Cognitive coefficient (Φ_1)	1.4900
	Social coefficient (Φ_2)	1.4900
	Max velocity (Vel_{max})	0.1000
	Min velocity (Vel_{min})	-0.1000
CSA	Population size (n_s)	1000
	Max iterations (t_{max})	5000
	Flight length (fl)	3.5000
	Awareness probability (AP)	0.0500
SSA	Population size (n_s)	10000
	Max iterations (t_{max})	20000
JAYA	Population size (n_s)	120
	Max iterations (t_{max})	5000

Table 6. Performance comparison of the optimization algorithms in economic and environmental terms

Algorithm	Best (USD)	Worst (USD)	Average (USD)	Std. Dev. (%)	Emissions (kg CO_2)
PSO	82 412.7817	83 331.6504	82 535.5323	0.1247	1901.6462
CSA	82 579.8546	84 130.9190	83 170.4159	0.4194	1908.5359
SSA	82 645.2949	83 943.2667	83 046.7009	0.3123	1892.3026
JAYA	83 192.7697	85 060.0251	83 742.7965	0.4241	1899.7974
Random	116 440.0000	—	—	—	1929.7846

Overall, for the 24-hour dispatch horizon considered, PSO achieved the best trade-off between economic and environmental objectives, providing a reliable and efficient solution for the thermal generator dispatch problem under the studied conditions.

Figure 3 displays the distribution of total generation costs obtained over 100 independent executions of each metaheuristic algorithm for the 24-hour economic dispatch problem. The boxplots allow visual comparison of the statistical behavior of the PSO, CSA, SSA, and JAYA algorithms.

As observed, PSO exhibits the most compact distribution, indicating high consistency and reliability in its solutions. The interquartile range is significantly narrower than that of the other algorithms, and its median value is the lowest among all methods, reaffirming its superior performance in minimizing operational cost. Moreover, the presence of minimal outliers further demonstrates the robustness of PSO.

On the other hand, JAYA presents the widest spread in total cost values, along with the highest median, reflecting a higher degree of variability and less favorable economic performance. CSA and SSA exhibit intermediate behavior, with moderate dispersion and median values situated between those of PSO and JAYA.

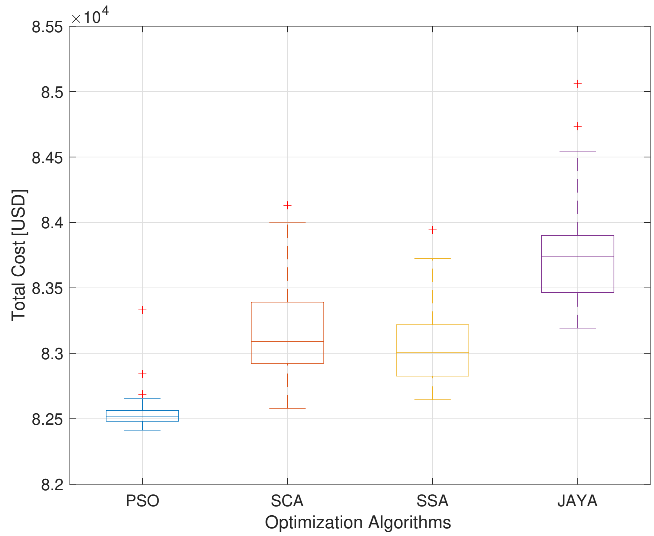

Figure 3. Boxplot of total generation cost (100 runs) for metaheuristic algorithms

Overall, the boxplot analysis supports the numerical results shown in Table 6, emphasizing the advantages of PSO in terms of both quality and repeatability for solving the economic dispatch problem under the given test conditions.

5.1. Performance Analysis of PSO-Based Economic Dispatch

Based on the comparative results discussed previously, this section presents a detailed analysis of the economic dispatch solution obtained using the PSO algorithm, which demonstrated the most favorable performance in terms of cost efficiency and robustness.

Firstly, we present in Figure 4 the cost savings achieved by the PSO algorithm in comparison to the best solutions obtained by other metaheuristics and a random baseline. PSO consistently delivers superior performance, with absolute cost reductions ranging from 167.0729 USD (CSA) to 779.9880 USD (JAYA), representing relative improvements of 0.2023% and 0.9376%, respectively. The most substantial improvement is observed against the random strategy, where PSO achieves a cost reduction of 34,027.2183 USD, corresponding to an improvement of approximately 29.2230%. These results confirm the effectiveness and robustness of PSO in minimizing generation costs across diverse optimization landscapes.

These differences highlight the superiority of PSO not only in minimizing the total cost associated with the thermal generation dispatch over a 24-hour operational horizon, but also in ensuring consistent performance across multiple independent runs

In Table 7, the hourly power output dispatched by each of the three thermal generators is reported, corresponding to the solution provided by the PSO algorithm. This detailed schedule allows for a clear examination of the operational behavior of each generation unit throughout the 24-hour period, including their individual contributions to satisfying the system demand.

Figure 5 illustrates the hourly generation profile of the three thermal units (G1, G2, and G3) over a 24-hour operating horizon, based on the solution obtained using the PSO algorithm. Each subplot displays the power output per hour (continuous line with markers) and the permissible operating range for each generating unit (shaded area), bounded by the respective minimum and maximum generation limits defined in Table 1.

The graphical analysis reveals a coherent and complementary operational pattern among the three generators, which reflects the effectiveness of the PSO algorithm in finding an economically yet technically feasible dispatch strategy. Generator G1 operates across a broad range of output levels, gradually ramping up its production in

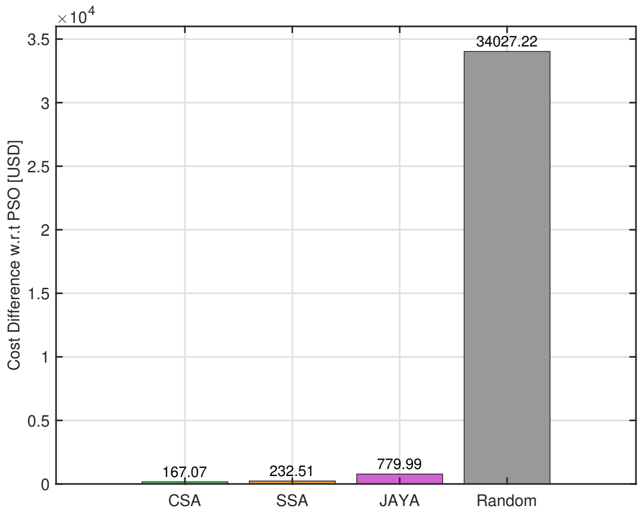

Figure 4. Comparative improvement in total operating cost with respect to PSO

Table 7. Hourly power output dispatched by each generator based on the PSO solution

Hour	G1 [MW]	G2 [MW]	G3 [MW]
1	41.2337	57.4473	116.6477
2	62.7014	60.4773	112.9460
3	45.5511	29.6727	129.7797
4	33.1734	54.8110	95.8912
5	62.9661	58.6715	125.1393
6	13.9471	50.2026	120.1385
7	31.0594	22.0884	99.6732
8	5.0000	15.0000	81.4222
9	5.0000	15.0000	60.8736
10	30.4109	15.0000	86.6935
11	45.3275	35.9206	113.1189
12	65.7419	67.1329	156.6486
13	79.5825	85.7939	156.0552
14	76.0107	58.5186	198.3861
15	95.8659	66.5640	202.6988
16	131.1571	76.3666	189.6231
17	124.3499	93.7507	201.0914
18	131.9306	100.0000	209.2791
19	125.2881	100.0000	250.0000
20	150.0000	100.0000	235.7898
21	147.2623	100.0000	250.0000
22	128.0144	100.0000	213.3103
23	98.4810	60.5436	206.1654
24	63.6646	49.0013	112.9533

response to rising demand and peaking near its upper limit during hours of maximum system load. Generator G2 exhibits a smoother and more centralized trajectory, primarily functioning within the midrange of its capacity, but reaching its technical maximum during high-demand periods, thus contributing additional flexibility to the system. Generator G3, with the highest nominal capacity, assumes the role of primary supplier during peak hours (particularly between hours 14 and 21), maintaining outputs close to its upper generation limit. The observed complementarity and coordinated behavior of the three units underline the intelligent balance achieved by PSO, ensuring cost-effective dispatch while strictly adhering to the operational limits of each generator.

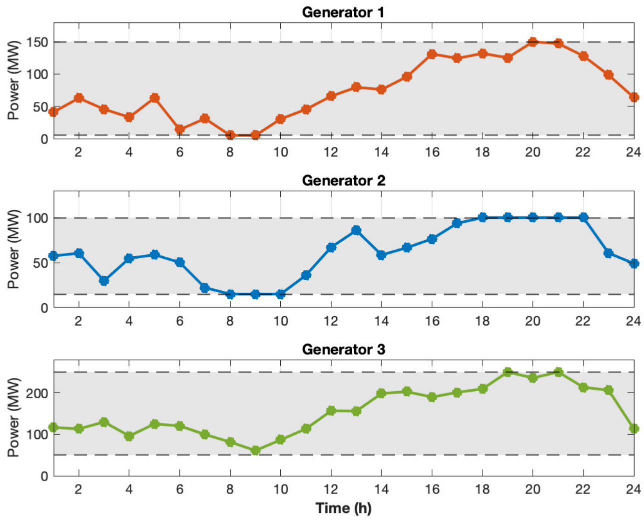

Figure 5. Hourly power output and operating limits for each generator

Figure 6 illustrates the comparison between the total power generated by the three thermal generating units (blue line) and the system's hourly demand (orange line) over a 24-hour operating horizon. It can be observed that generation consistently exceeds demand throughout all time periods, with no deficit occurring at any hour.

This excess generation does not indicate inefficient overproduction; rather, it is deliberately incorporated to compensate for the technical power losses inherent in the electrical system, as established in Equation (4). The green shaded area highlights these overgeneration margins, which are necessary to ensure that the energy delivered to the load nodes fully satisfies the actual demand. This dispatch strategy demonstrates a technically feasible operation, fulfilling system constraints while reflecting the realistic characteristics of an electrical power system. Consequently, the generation schedule not only meets the load requirements but also offsets the system's intrinsic losses.

The results obtained demonstrate the effectiveness of the proposed optimization framework based on the Particle Swarm Optimization algorithm to the economic dispatch problem of thermal generation units yielded technically feasible and economically efficient results. Among the four compared strategies—including four metaheuristic algorithms (PSO, CSA, SSA, JAYA) and a randomly generated baseline—PSO consistently achieved the lowest total generation cost, with a best-case value of \$82,412.7817 and a relative standard deviation of just 0.1247%, indicating high repeatability and solution stability. Furthermore, PSO maintained a competitive CO_2 emission level of 1,901.6462 kg, reflecting a favorable cost–emissions trade-off.

The hourly dispatch schedule obtained with PSO adheres strictly to the operational constraints of each generating unit. The dispatch solution dynamically distributes the power output among the three generators, leveraging their capabilities to meet hourly demand requirements while respecting minimum and maximum generation limits. In particular, G1 exhibited flexible ramping behavior, G2 operated mostly in the mid-range of its capacity, and G3 assumed the highest load responsibility during peak hours.

Additionally, the total hourly generation surpassed the demand curve in all time periods, without any occurrence of supply deficit. This overgeneration is not incidental; it is explicitly intended to compensate for technical power losses in the system, ensuring that the net energy delivered to the load points satisfies the actual demand. Graphical

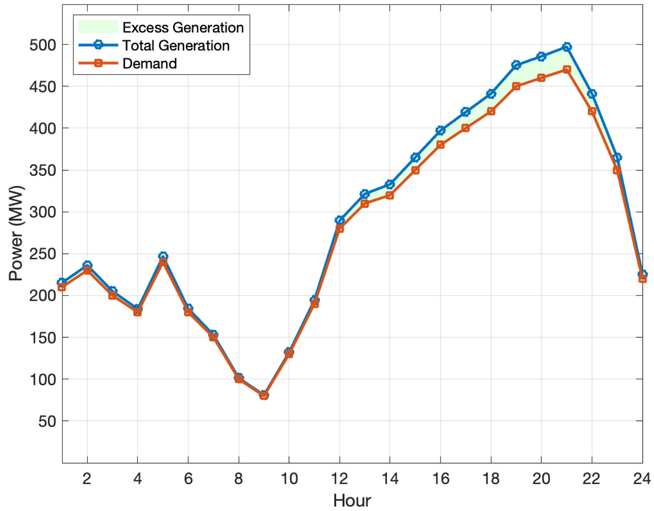

Figure 6. Comparison of total generation vs demand

analyses further confirm that the dispatch solution is both feasible and realistic, highlighting the capability of PSO to generate reliable and high-quality operational strategies for power system management.

6. Conclusions and future work

This study addressed the economic dispatch problem of thermal generators by implementing and evaluating four metaheuristic optimization algorithms: Particle Swarm Optimization, Crow Search Algorithm, Salp Swarm Algorithm, and JAYA. The complexity of the problem—stemming from its nonlinear, nonconvex, and multimodal nature—demonstrates the relevance of adopting advanced computational techniques for modern power systems, where efficient energy management is crucial given increasing operational demands and technological integration.

The comparative analysis revealed that all four algorithms achieved high-quality solutions, significantly outperforming the randomly generated baseline, which yielded an excessive total dispatch cost of \$116,440.0000. Among the tested techniques, PSO stood out by achieving the lowest total generation cost (\$82,412.7817) and exhibiting the highest consistency, with a relative standard deviation of just 0.1247%. In contrast, the JAYA algorithm presented the highest cost (\$83,192.7697) but also achieved one of the lowest CO_2 emissions profiles (1,899.7974 kg CO_2), highlighting trade-offs between economic and environmental performance.

Despite these differences, all four metaheuristics demonstrated robustness and effectiveness, delivering feasible and technically compliant solutions. This underscores their suitability for solving real-world economic dispatch problems, especially when contrasted with the inefficiency of non-optimized approaches. The intelligent allocation strategies enabled by the algorithms ensured compliance with generator operating limits, effective load tracking, and the inclusion of technical power losses—factors critical for the reliable and economic operation of electrical power systems.

Although the proposed study provides valuable insights into the performance of bio-inspired optimization algorithms for thermal economic dispatch, several limitations must be acknowledged. First, the model assumes a simplified single-node system without network constraints such as voltage limits or line capacities. Second, operational dynamics such as ramp rate constraints, minimum up/down times, and unit commitment decisions are not considered. Third, the emission evaluation is performed post-optimization rather than being embedded in a multi-objective framework. These simplifications allow for a focused comparison of algorithmic performance but may limit the direct applicability of results to real-world systems.

For this reason, as a projection for future work, it is proposed to extend the economic dispatch problem toward a multi-objective optimization approach that simultaneously minimizes operating costs, pollutant emissions, and improves power system performance using technical indicators such as voltage profiles or system reliability. Additionally, it is recommended to incorporate non-dispatchable renewable energy sources, such as solar photovoltaic or wind power, whose temporal variability introduces uncertainty and requires the use of more advanced techniques, such as stochastic or robust optimization. Another research direction involves explicitly considering network constraints—including line flow limits and nodal voltage restrictions—in order to more realistically represent system operating conditions, thereby transforming the problem into a Constrained Economic Dispatch formulation. Finally, exploring hybrid or cooperative metaheuristic strategies, which combine the strengths of different techniques such as PSO and JAYA, is suggested to enhance both solution quality and computational robustness.

In summary, the results confirm the practical applicability of metaheuristic optimization in addressing complex operational challenges in power systems, providing a solid foundation for further research into hybrid models, multi-objective formulations, and integration with renewable resources under dynamic grid conditions.

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