

OPTIMAL ECONOMIC DISPATCH OF THERMAL POWER GENERATION CONSIDERING LOSSES USING PARTICLE SWARM OPTIMIZATION (PSO)

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ABSTRACT

To set the daily schedule for thermal units under rising industrial loads in Vietnam, we calculate the economic dispatch (ED) on a 26-bus grid using a modified version of Particle Swarm Optimization (PSO). Active power losses are calculated from the B-coefficients of Kron. Instead of scattering initial particles at random across the operating limits, we only modify the starting equation to weight each position by the fuel cost of that unit at half capacity. Early iterations are reduced because the swarm starts near cheaper units. On the 26-bus test grid, we reduce the total fuel cost to \$15,689.411 per hour, which is lower than the costs from random PSO and from the method of Lagrange multipliers. Transmission losses across the network are cut to 26.091 MW.

Keywords: Economic dispatch, particle swarm optimization, transmission loss, B-coefficient method, population initialization strategy.

1. INTRODUCTION

Because industrial loads in Vietnam raise the operating cost of thermal plants, we solve the problem of Economic Dispatch (ED) to set the real power of each online unit at minimum fuel cost. Generator outputs are bounded by total load, line losses, and capacity limits.

When we apply the method of Lagrange multipliers [1] to this power allocation, we must calculate partial derivatives of the cost and loss functions to solve the coordination equations in each iteration. Exact solutions are obtained only when the grid model is simplified. If curves of fuel cost are nonlinear or loss matrices grow dense in larger grids, this study notes that derivative solvers like the Newton–Raphson method require more iterations to update the power variables. The operating points of the units are trapped at local minima.

To bypass the calculation of derivatives, this study examines heuristic routines for the ED problem, including the Genetic Algorithm [2], Ant Colony Optimization [3], Tabu Search [4], and Hopfield networks [5]. The dispatch schedule is also solved by Particle Swarm Optimization (PSO) [6].

When we apply the PSO algorithm of Kennedy and Eberhart [6] to mimic foraging flocks, we evaluate the cost function directly with few control weights under loss equations and unit limits. In standard PSO, the starting positions of particles are set randomly. Because these random particles start far from low-cost regions across the multidimensional space of a lossy grid, we must run more iterations before the power variables converge toward a dispatch solution. The final operating point is frequently trapped at a local minimum.

To solve the lossy ED problem on the 26-bus grid, we calculate real power losses from the B-coefficients of Kron and modify the starting phase of the swarm. Initial positions are weighted by the fuel cost at mid-range output. Through this cost ratio, this study sets the initial output of cheaper thermal units near their upper generation limits at iteration zero instead of using uniform random numbers. More expensive units are placed near their minimum power bounds.

When we compare this cost-weighted initialization on the 26-bus network with random PSO and the method of Lagrange multipliers, we obtain a dispatch schedule in a smaller iteration count k . Both hourly fuel cost F and grid loss P_L are reduced. Because this weighting rule only modifies initial variables before the search loop, we can apply the same initialization to larger hydrothermal grids and power networks with renewable sources in Vietnam. Daily dispatch schedules are updated within fewer calculation cycles k .

2. ECONOMIC DISPATCH OF THERMAL POWER PLANTS USING THE LAGRANGE METHOD

2.1. Model of economic dispatch

Because power dissipates along the transmission lines, we formulate the problem of economic dispatch to calculate the active power of each thermal unit at the lowest total cost of fuel. These variables are bounded by the balance equation and limits of capacity.

$$\text{Min } C_{total} = \sum_{i=1}^n C_i = \sum_{i=1}^n (\alpha_i + \beta_i P_i + \gamma_i P_i^2) \quad (1)$$

Where:

- $\alpha_i, \beta_i, \gamma_i$ are the cost coefficients of generator i .
- P_i is the power output of generator i .

The power balance constraint considering transmission losses is given by:

$$\sum_{i=1}^n P_i = P_D + P_L \quad (2)$$

Where:

- P_D is the total load demand of the system.
- P_L is the real power loss during transmission.

Generator output limit constraint:

$$P_{imin} \leq P_i \leq P_{imax} \quad (3)$$

2.2. Economic dispatch solution using the Lagrange method

The Lagrange method is a classical approach used to solve the constrained ED problem. The extended Lagrangian function is formulated as follows:

$$L = \sum_{i=1}^n C_i(P_i) + \lambda \left(P_D + P_L - \sum_{i=1}^n P_i \right) \quad (4)$$

Taking the partial derivatives of L with respect to P_i and λ , we obtain the necessary conditions for determining the optimal solution:

$$\frac{\partial L}{\partial P_i} = \frac{dC_i}{dP_i} + \lambda \left(\frac{\partial P_L}{\partial P_i} - 1 \right) = 0 \quad (5)$$

$$\frac{\partial L}{\partial \lambda} = P_D + P_L - \sum_{i=1}^n P_i = 0 \quad (6)$$

Here, the partial derivative of the transmission loss is defined as:

$$\frac{\partial P_L}{\partial P_i} = 2 \sum_{j=1}^n B_{ij} P_j + B_{0i} \quad (7)$$

The Newton–Raphson iterative method is employed to update the values of λ and P_i in each iteration until the power balance error becomes smaller than a specified threshold:

$$\Delta P = P_D + P_L - \sum_{i=1}^n P_i < \varepsilon \quad (8)$$

2.3. Transmission loss model using the B-coefficient method

The real power loss in the system is modeled using the B-coefficient method [7] (also known as the Kron loss formula), expressed as:

$$P_L = \sum_{i=1}^n \sum_{j=1}^n P_i B_{ij} P_j + \sum_{i=1}^n B_{0i} P_i + B_{00} \quad (9)$$

Alternatively, it can be written in matrix form as:

$$P_L = P^T B_{ij} P + P^T B_{0j} + B_{00} \quad (10)$$

Where:

- B_{ij} : Loss coefficient between generation units i and j .
- B_{0i} : Loss coefficient associated with unit i .
- B_{00} : Constant loss coefficient.
- n : Number of generating units.
- P_i, P_j : Power outputs of units i and j .

3. ECONOMIC DISPATCH OF THERMAL POWER PLANTS USING THE PSO METHOD

3.1. Overview of particle swarm optimization

3.1.1. Introduction

To solve complex grid constraints, researchers test search routines like neural networks [5], fuzzy systems [7], and genetic algorithms [2] from the field of artificial intelligence [8]. The particle swarm of Kennedy and Eberhart [6] is also applied. Because this algorithm evaluates the objective function without partial derivatives, we use it to schedule the economic dispatch of power systems [9], [10]. Coordinate vectors are moved according to biological foraging rules. As we run the search loop, each particle updates its own location from local spatial memory and the global distance of the entire swarm. Multidimensional variables are calculated through simple arithmetic steps. We scatter the initial candidates at random across the feasible limits and calculate a velocity vector to shift the spatial coordinates in every cycle. The minimum cost F is reached after evaluating the fitness function.

3.1.2. Advantages and disadvantages

Because the swarm algorithm does not calculate partial derivatives, we evaluate non-differentiable boundaries directly to avoid the heavy processing loads of gradient models [6], [10]. Calculation cycles are reduced for the dispatch problem. When we expand the search dimensions of the power system, coordinate vectors often fall into local optima because standard particles stagnate in the spatial grid. The convergence velocity drops during the calculation steps. To fix these algorithmic bottlenecks, researchers must change the internal structure of the swarm by controlling adaptive parameters or mixing different configuration models during the search process. Hybridized swarms are deployed to avoid the local minimum.

3.1.3. Practical applications

Since the swarm calculates multiple objective constraints, we apply this logic to tune control parameters across nonlinear equations instead of just dispatching power grids [11]. Neural networks and support vector machines are optimized [12]. Researchers also set physical resource limits for engineering system designs [10] and structure financial portfolios by converting the basic search mechanism into quantitative mathematical equations. Complex medical data is classified into discrete groups.

3.2. Solution for economic dispatch

Because the dispatch problem uses real variables, we set each coordinate vector as a moving particle inside the operating limits. A vector $X_i \in \mathbb{R}^n$ sets the position of the particle. The operating point is updated by a velocity vector $V_i \in \mathbb{R}^n$. Equation (11) calculates the coordinate sequence of each generator [13]:

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)} \quad (11)$$

When we run the search loop, we adjust the output power of the unit according to its own local memory and the global distance of the swarm. The swarm shares spatial coordinates. Because the mathematical pull from the local memory and global optimum changes over time, this study sets random control parameters to weight the vectors. A new velocity is calculated to shift the particles. Equation (12) sets the acceleration values for the next iteration [13]:

$$V_i^{(t+1)} = w \cdot V_i^{(t)} + c_1 \cdot rand_1 \cdot (Pbest_i - X_i^{(t)}) + c_2 \cdot rand_2 \cdot (Gbest_i - X_i^{(t)}) \quad (12)$$

Where:

- $V_i^{(t)}$: Velocity of particle i at iteration t .
- $X_i^{(t)}$: Position of particle i at iteration t .
- w : Inertia weight.
- c_1 : Cognitive learning coefficient.
- c_2 : Social learning coefficient.
- $rand_1, rand_2$: Random numbers in the range $[0, 1]$.
- $Pbest_i$: The best position found by particle i based on its own experience.
- $Gbest$: The best position discovered by the entire swarm.

When we calculate the velocity of the swarm, we divide Equation (12) into three driving forces [13]. The previous velocity is retained by the inertia weight. Because the algorithm must balance local searches and global exploration, this study sets a cognitive parameter to pull the particle toward its own best position (P_{best}). The coordinate vector is also guided by the global optimum (G_{best}). We calculate these velocity values in every loop and substitute them into Equation (11) to shift the spatial positions of the generators. The final trajectory is calculated from prior momentum and swarm data.

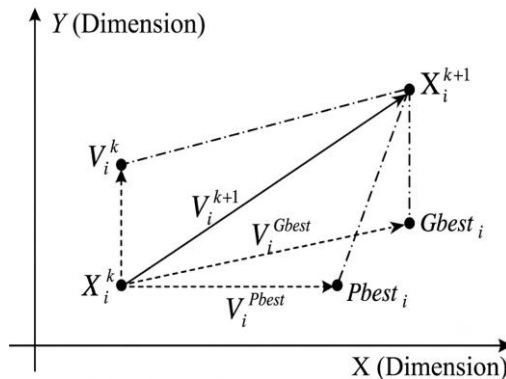


Figure 1. Direction of movement of each particle

The PSO algorithm can be implemented using the following flowchart (Figure 2):

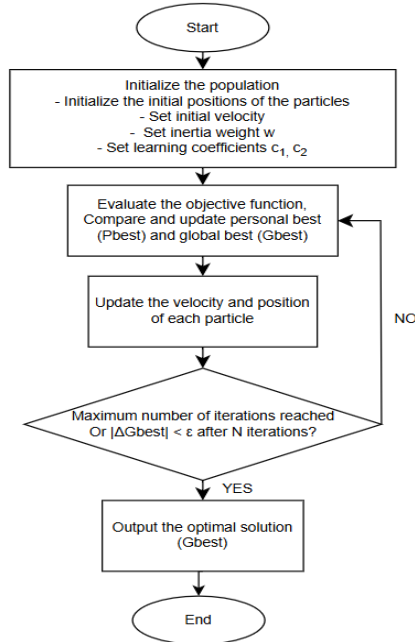


Figure 2. Flowchart of the PSO algorithm

4. OPTIMAL ECONOMIC DISPATCH OF THERMAL POWER PLANTS IN THE 26-BUS POWER SYSTEM

Computational execution of this economic dispatch framework maps directly onto the procedural architecture detailed in Figure 3.

A 26-bus power system is modeled as shown in Figure 4 [1].

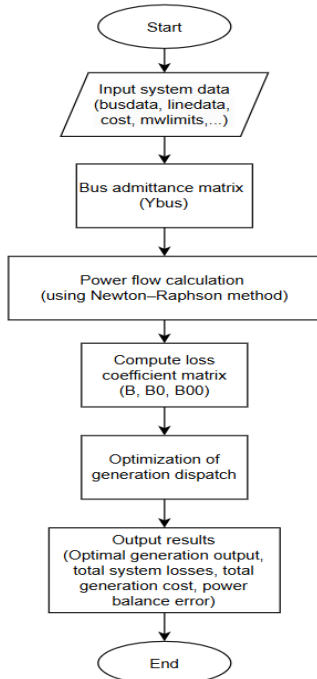


Figure 3. Flowchart of the proposed ED program for the IEEE 26-bus system

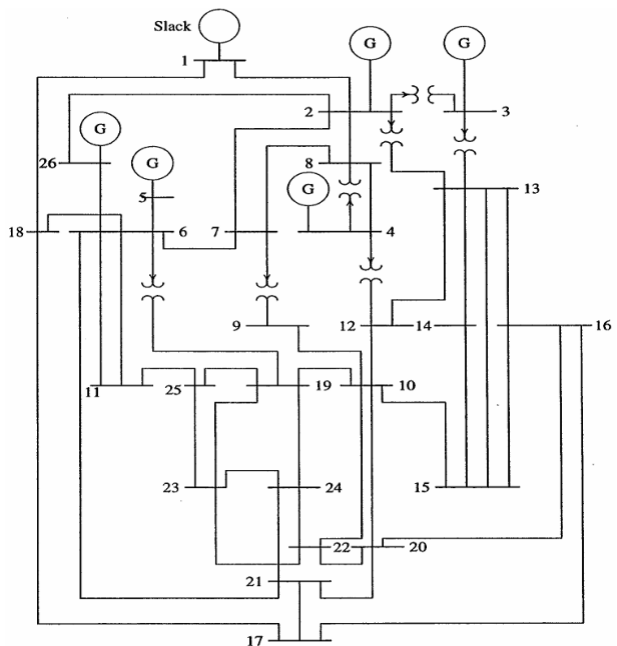


Figure 4. Single-line diagram of the IEEE 26-bus system

Bus 1 is taken as the slack bus with its voltage adjusted to $U = 1.025 \angle 0^\circ$ p.u. Determine the optimal dispatch of generation when the total system load is 1263 MW [1].

Table 1. Regulated bus data

Regulated bus data			
Bus No.	Voltage Magnitude	$Q_{\min}$ (Mvar)	$Q_{\max}$ (Mvar)
2	1.02	40	250
3	1.025	40	150
4	1.05	40	80
5	1.045	40	160
26	1.015	15	50

Table 2. Transformer data

Transformer data	
Transformer Designation	Tap Setting Per Unit
2 - 3	0.96
2 - 13	0.96
3 - 13	1.017
4 - 8	1.05
4 - 12	1.05
6 - 19	0.95
7 - 9	0.95

Table 3. Shunt capacitor data

Shunt capacitor data	
Bus No.	Mvar
1	4
4	2
5	5
6	2
9	3
11	1.5
12	2
15	0.5
19	5

The generator operating cost functions are as follows:

$$C_1 = 240 + 7P_1 + 0.007P_1^2 (\$/h)$$

$$C_2 = 200 + 10P_2 + 0.0095P_2^2 (\$/h)$$

$$C_3 = 220 + 8.5P_3 + 0.009P_3^2 (\$/h)$$

$$C_4 = 200 + 11P_4 + 0.009P_4^2 (\$/h)$$

$$C_5 = 220 + 10.5P_5 + 0.008P_5^2 (\$/h)$$

$$C_{26} = 190 + 12P_{26} + 0.0075P_{26}^2 (\$/h)$$

The real power output limits of the generating units in the 26-bus power system are summarized in Table 4:

Table 4. Generator real power limits

Generator real power limits		
Gen	$P_{\min}$ (MW)	$P_{\max}$ (MW)
1	100	500
2	50	200
3	80	300
4	50	150
5	50	200
26	50	120

4.1. Assumptions and simulation conditions

Because the parameters of the 26-bus grid are fixed, we calculate the power flow from the resistance and reactance of the transmission lines. The loss matrix B_{loss} is calculated from these network variables. We model the fuel cost of each thermal unit as a quadratic function and set the real power within the minimum and maximum limits (P_{min}, P_{max}). Transmission losses are approximated through this coefficient matrix. Since we calculate this matrix from the initial power flow and the grid structure, we can skip the full AC equations during the search loops [1], [14]. The total load demand P_d remains constant during the simulation.

4.2. Application of the Lagrange method

When we apply the method of Lagrange multipliers to this power network, we list the final values of the dispatch schedule in the first column of Table 5.

4.3. Application of the PSO method

The swarm algorithm is executed according to the flowchart in Figure 3. To optimize the generation output of the thermal units, this study configures the coordinate vectors and updates the power variables through the detailed loop in Figure 5.

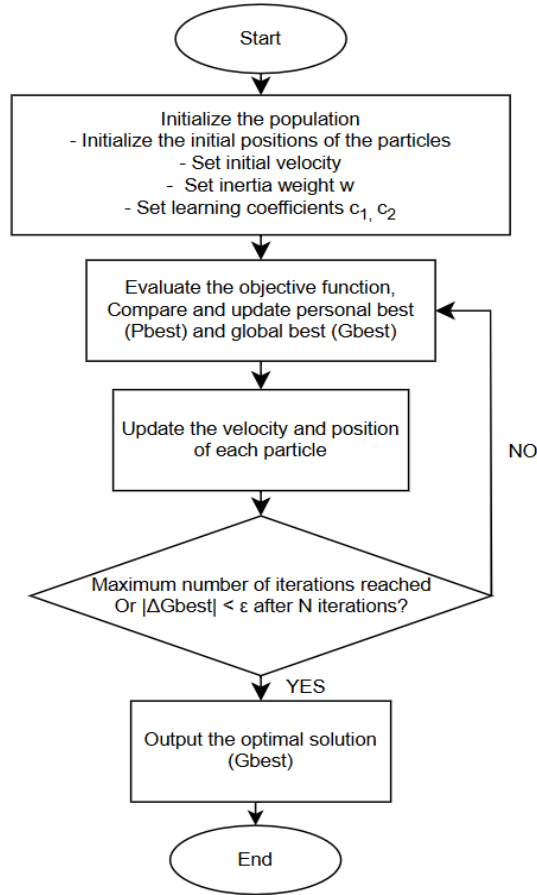


Figure 5. Flowchart of the PSO-based algorithm for ED calculation in the 26-bus power system

4.3.1. Initialization from cost weights

When we set the initial coordinates of the swarm across the limits using random numbers, we ignore the physical cost parameters of each thermal unit. The search vectors are trapped in high-cost regions. Because these random positions slow down the search loop in multidimensional grids, this study sets a starting weight from the fuel data of each generator. Spatial boundaries are restricted early.

To calculate the relative cost ratio for the swarm algorithm, we test the exact fuel output at the midpoint capacity of the thermal unit. The baseline cost is calculated from a quadratic polynomial:

$$C_i = \alpha_i + \beta_i \cdot \frac{P_{i,max} + P_{i,min}}{2} + \gamma_i \cdot \left(\frac{P_{i,max} + P_{i,min}}{2} \right)^2 \quad (13)$$

We normalize these numerical values across the entire grid to extract a relative cost ratio for each thermal generator before we start the search loops. Equation (14) calculates this relative fraction.

$$cost_factor_i = \frac{C_i}{\sum C_i} \quad (14)$$

To set the starting coordinates of the swarm, we calculate the initial position X_i of each particle from the extracted cost ratio. Equation (15) sets this position X_i .

$$X_i = P_{i,min} + (P_{i,max} - P_{i,min}) \cdot (rand \cdot (1 - cost_factor_i) + cost_factor_i) \quad (15)$$

Because we embed this mathematical ratio into the algorithm, we force cheaper generators toward their upper limits P_{max} and restrict expensive units near P_{min} . The search volume is physically shrunk. Since this setup calculates initial coordinates X_i inside the viable operating zone, we avoid purely random scattering and balance spatial exploration with local exploitation. Random variables preserve the diversity. Because we filter out early computational waste without changing the core kinematic equations, the number of iterations k for terminal convergence is reduced. Figure 6 plots the performance trajectories. When we pre-align the swarm memory with the unit economics on the network, we measure steeper gradients of convergence and lower the fuel cost F in Table 5.

4.3.2. Algorithmic configuration and comparative execution

Because the dispatch equations are non-linear, we set a dense population of 1500 spatial particles to cover the operating limits of the thermal generators. The inertia weight is decreased from 0.9 to 0.4. Since this weight reduces over time, we shift the search coordinates from wide-area exploration to local exploitation. The cognitive parameter is set to 1.5. We also fix the social component at 2.0 to pull the coordinate vectors toward the global optimum instead of using symmetrical acceleration coefficients. These control parameters are tested on the 26-bus grid. When we calculate the operational profiles using this matrix, we compare the cost-guided initialization in Column 2 with the standard random variables in Column 3 of Table 5.

4.4. Performance evaluation of PSO with the Proposed Initialization Strategy

Table 5. Comparison of ED results for the IEEE 26-bus system using different methods

	Lagrange	PSO (Proposed Initialization Strategy)	PSO
Total system losses (MW)	26.1565	26.091	28.399
Total generation output (MW)	1289.1564	1289.09	1291.3994
Power balance error (MW)	0.000018	0.00099	0.00039
Total generation cost (\$/h)	15689.454	15689.411	15711.002

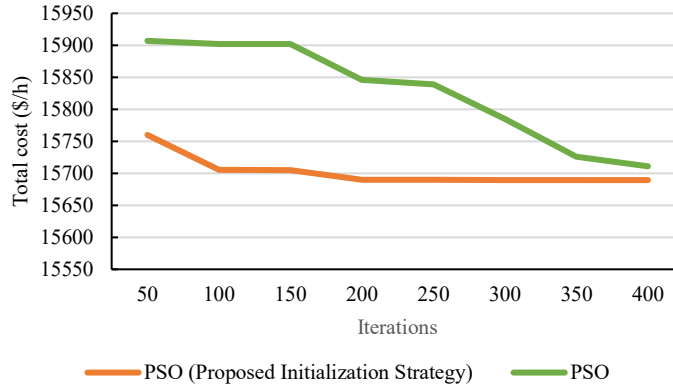


Figure 6. Convergence comparison of total generation cost between the proposed and standard PSO on the IEEE 26-bus system

From the numerical outputs in Table 5, we reduce the generation cost to \$15,689.411 per hour and cut the transmission loss to 26.091 MW by using the cost-guided swarm. The power balance error ΔP is recorded at 0.00099 MW. Because this study sets initial positions from generator cost ratios before enforcing the power balance equation, we observe a larger residual mismatch during early iterations than the 0.000018 MW from the Lagrange method and the 0.00039 MW from standard PSO. This power mismatch stays below the 0.001 MW operating limit.

When the swarm starts without cost weights in standard PSO, we obtain a higher generation cost of \$15,711.002 per hour and a larger transmission loss of 28.399 MW. The convergence curves are compared in Figure 6. In this figure, we see that the cost-weighted positions lower the total cost curve at a steeper slope and converge in fewer iterations k than the random swarm. The optimal power output P_i is obtained for each thermal unit on the lossy network.

5. CONCLUSION

In this study, we modify the initialization step of the PSO algorithm to solve the lossy economic dispatch problem for thermal generating units. Initial particle positions X_i are weighted by the fuel cost of each unit at half capacity. Because the swarm starts near lower-cost regions instead of using uniform random numbers, we avoid unnecessary evaluations in high-cost zones and reduce the number of iterations to converge.

When we test this initialization on the 26-bus grid with the B-coefficient loss matrix of Kron, we reduce the hourly fuel cost to \$15,689.411 per hour and cut line losses to 26.091MW compared to standard PSO and the Lagrange multiplier method. The power balance mismatch is kept below 0.001MW.

This approach preserves the standard PSO loop structure without introducing extra computational steps per iteration. The proposed equation is applied directly to nonlinear cost functions without taking partial derivatives like the Lagrange solver. In future tests, we can apply this cost-ratio rule to larger power networks and grids with renewable generators.

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Additional information

Author contributions

All authors contributed equally to the study conception, methodology, analysis, and manuscript preparation. All authors read and approved the final manuscript.

Conflict of interest

The authors declare that they have no conflict of interest and no affiliations with or involvement in any organization or entity with any financial interest in the subject matter or materials discussed in this manuscript.

Artificial Intelligence (AI) use

During the preparation of this manuscript, the authors used Grammarly and ChatGPT to assist with language editing, grammar correction, and readability improvement. Following this process, the authors thoroughly reviewed and revised the resulting content and assume full responsibility for the entirety and integrity of the published work.

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