Multi-Objective Economic–Environmental Dispatch Using Particle Swarm Optimization and Pareto Analysis

P. Vinod Kumar[1], Swetha Reddy Dwarsala[2], Y Sasidhar Kumar Yadav[3], Kalle Nagavardhan[4], K Sai Krishna[5], E Yadunandana Reddy[6]

[1,2,3,4,5,6]Dept. of EEE, Sri Venkateswara College of Engineering, Tirupati, Andhra Pradesh, India

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Abstract - Economic–Environmental Dispatch (EED) is a key optimization problem in modern power systems that aims to minimize fuel cost and emission while satisfying operational constraints. This paper investigates the EED problem for a five-generator thermal power system using Particle Swarm Optimization (PSO). The fuel cost and emission of generating units are modelled using quadratic functions, and generator operating limits and power balance constraints are considered. The performance of the proposed PSO approach is compared with a conventional base optimization method under different dispatch scenarios. Six case studies are analyzed, including economic dispatch, emission dispatch, penalty-based optimization, emission-constrained dispatch, Pareto front generation, and load variation analysis. The results demonstrate that PSO provides slightly improved or comparable solutions in terms of generation cost and emission compared to the base method. Furthermore, the Pareto front analysis illustrates the trade-off between economic and environmental objectives, while load variation analysis confirms the robustness of PSO under different demand conditions. The study shows that PSO is an effective and reliable optimization technique for solving the Economic–Environmental Dispatch problem.

Key Words: Economic–Environmental Dispatch, Particle Swarm Optimization, Fuel Cost, Emission, Pareto Front, Load Variation.

1.INTRODUCTION

Economic Load Dispatch (ELD) is a fundamental optimization problem in power system operation that aims to determine the optimal generation schedule while minimizing fuel cost and satisfying operational constraints. Early work by Liang and Glover [1] introduced dynamic programming approaches considering transmission losses, while Lee and Breipohl [2] addressed reserve-constrained economic dispatch with prohibited operating zones. Walters and Sheble [3] further improved solution methodologies by applying genetic algorithms to handle valve-point loading effects in non-smooth cost functions.

Subsequently, multi-objective environmental economic dispatch problems were addressed using modern optimization techniques such as Grey Wolf Optimization [4], while combined heat and power (CHP) based dispatch strategies were developed to enhance overall system efficiency [5]. Evolutionary programming approaches were introduced for solving environmentally constrained economic dispatch problems [6], followed by homogeneous linear programming techniques for security-constrained economic dispatch [7].

Recent developments include the application of Starfish Optimization for solving economic emission dispatch problems under uncertainty and renewable energy integration [8]. Particle Swarm Optimization (PSO) has been widely adopted for solving economic dispatch problems with non-smooth cost characteristics [9], along with improved genetic algorithms for handling valve-point effects and multiple fuel options [10]. The foundational concept of Particle Swarm Optimization was introduced by James Kennedy and Russell Eberhart [11].

Furthermore, Ant Lion Optimization techniques have been effectively applied to solve economic load dispatch problems under practical constraints [12], [13]. PSO-based approaches have also been extended to solve short-term hydrothermal scheduling problems [14]. The integration of renewable energy resources has been addressed through coordinated operation of wind generation and pumped-storage hydro units [15], as well as optimization of wind-integrated power systems using advanced techniques [16].

To address system uncertainties, stochastic economic dispatch models have been proposed [17]. Multi-objective environmental economic dispatch problems have also been revisited using optimization techniques such as Grey Wolf Optimization [18]. Additionally, decentralized optimization approaches have been developed to improve scalability and operational efficiency in modern power systems [19]. More recently, mountaineering team-based optimization techniques have been introduced for solving economic load dispatch problems under realistic operating constraints [20].

Advanced modeling tools such as GAMS have been widely used for solving complex power system optimization problems due to their flexibility and computational efficiency [21].

Despite significant advancements, achieving an optimal trade-off between economic and environmental objectives under varying operating conditions remains a challenging task. Therefore, this paper focuses on solving the Economic–Environmental Dispatch problem for a five-unit thermal power system using conventional methods and Particle Swarm Optimization. Six case studies are considered, including economic dispatch, emission dispatch, penalty-based dispatch, emission-constrained dispatch, Pareto front generation, and load variation analysis.

2. PROBLEM FORMULATION

2.1 Economic–Environmental Dispatch Model

Economic–Environmental Dispatch (EED) is an important optimization problem in power system operation. The objective is to determine the optimal power generation schedule of committed generating units while minimizing the fuel cost and emission levels under operational constraints.

In this study, a five-generator thermal power system is considered. The optimization aims to determine the optimal generator outputs that satisfy load demand while maintaining generator operating limits.

2.2 Fuel Cost Function

The fuel cost function of a thermal generator is generally approximated by a quadratic polynomial as follows:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \quad (1)$$

where

- $F_i(P_i)$ = fuel cost of the ith generator ($/hr)
- P_i = output power of generator i (MW)
- a_i, b_i, c_i = fuel cost coefficients of generator i

The total fuel cost of the system is given by

$$F_{total} = \sum_{i=1}^{24} \left(a_i P_i^2 + b_i P_i + c_i \right) \quad (2)$$

where N represents the number of generating units.

2.3 Emission Function

Thermal power plants produce harmful emissions such as NO_x and SO_2. The emission function is also modelled using a quadratic function:

$$E_i(P_i) = d_i P_i^2 + e_i P_i + f_i \quad (3)$$

where

- $E_i(P_i)$ = emission produced by generator i
- d_i, e_i, f_i = emission coefficients.

The total emission of the system is

$$E_{total} = \sum_{i=1}^{24} \left(d_i P_i^2 + e_i P_i + f_i \right) \quad (4)$$

2.4 Objective Functions

The EED problem involves different optimization scenarios.

Economic Dispatch: $\min F_{total}$

Emission Dispatch: $\min E_{total}$

To obtain a compromise between fuel cost and emission, a penalty factor method is used. The combined objective function is expressed as

$$F = F_{total} + \lambda E_{total} \quad (5)$$

Where, λ is the emission penalty factor that converts emission units into cost.

2.5 Constraints

Power Balance Constraint: The generated power must satisfy the load demand.

$$\sum_{i=1}^{N} P_i = P_D \quad (6)$$

Where, P_D = total system demand.

Generator Capacity Limits: Each generating unit operates within its minimum and maximum limits.

$$P_i^{min} \le P_i \le P_i^{max} \quad (7)$$

Emission Constraint: In emission-constrained dispatch, the total emission must satisfy

$$E_{total} \le E_{limit} \quad (8)$$

where E_{limit} is the allowable emission level.

3. PARTICLE SWARM OPTIMIZATION FOR EED

3.1 Overview of Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based stochastic optimization technique introduced by Kennedy and Eberhart. The algorithm is inspired by the collective behaviour of bird flocking and fish schooling.

In PSO, each candidate solution is represented as a particle in the search space. The particle adjusts its position by learning from:

1. its personal best experience
2. the global best solution found by the swarm.

Due to its simple structure and strong global search capability, PSO has been widely applied in solving economic dispatch and multi-objective power system optimization problems.

3.2 Particle Representation

In the EED problem, each particle represents a possible generator schedule:

$$X_i = [P_1, P_2, P_3, \ldots, P_N] \quad (9)$$

where

P_i represents the power output of generator i.

3.3 Velocity Update Equation

The particle velocity is updated using the following equation:

$$v_i^{t+1} = w v_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t) \quad (10)$$

where

- v_i = particle velocity
- x_i = particle position
- $pbest_i$ = personal best position
- gbest = global best position
- w = inertia weight
- c_1, c_2 = acceleration coefficients
- r_1, r_2 = random numbers between 0 and 1.

3.4 Position Update Equation

The particle position is updated according to

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (11)$$

After updating, the particle position is adjusted to satisfy generator limits and power balance constraints.

3.5 PSO Algorithm Procedure

The PSO algorithm for solving the EED problem is summarized as follows:

1. Initialize particle positions within generator limits.
2. Initialize particle velocities randomly.
3. Evaluate the objective function for each particle.
4. Store the personal best solution of each particle.
5. Identify the global best solution among all particles.
6. Update particle velocities using the velocity equation.
7. Update particle positions.
8. Enforce generator operating limits and power balance constraint.
9. Repeat steps 3–8 until the maximum iteration is reached.
10. The global best particle represents the optimal generator schedule.

Table 1 comparing PSO parameters and ELD parameters.

Table 1: Comparison of ELD Parameters and PSO Parameters

Parameter	Symbol	Description	Typical Value
Population size	N_p	Number of particles in swarm	50 – 100
Maximum iterations	MaxIter	Stopping criterion	200 – 500
Inertia weight	w	Controls exploration vs exploitation	0.4 – 0.9
Cognitive coefficient	c_1	Self-learning component	2
Social coefficient	c_2	Swarm learning component	2
Particle velocity	v_i	Movement direction of particle	Updated each iteration
Particle position	x_i	Candidate solution (generator outputs)	$P_1, P_2, P_3, \ldots, P_N$
Personal best	p_{best}	Best solution found by particle	Stored value
Global best	g_{best}	Best solution in swarm	Optimal solution

4. RESULTS AND DISCUSSION

4.1 Test System Description

In this study, a five-generator thermal power system is considered to analyse the Economic–Environmental Dispatch (EED) problem. The generator data include fuel cost coefficients, emission coefficients, and generator operating limits. These parameters are used to calculate the total generation cost and emission of the system while satisfying the power demand and generator constraints. The generator cost coefficients, emission coefficients, and operating limits used in this study are presented in Table 2.

To evaluate the effectiveness of the optimization approach, the results obtained using the base optimization method are compared with those obtained using the Particle Swarm Optimization (PSO) algorithm under different operating scenarios. For Cases 1–4, the total system load demand is fixed at 400 MW. The performance of the base method and the PSO algorithm is evaluated under different dispatch scenarios, and the corresponding generator outputs, total cost, and emission values are presented in Table 3.

Table 2. Generator Cost and Emission Data for the Test System

Generator	G1	G2	G3	G4	G5
$a_i\left(\frac{\$}{MW^2}\right)$	3	4.05	4.05	3.99	3.88
$b_i\left(\frac{\$}{MW}\right)$	20	18.07	15.55	19.21	26.18
$c_i(\$)$	100	98.87	104.26	107.21	95.31
$d_i\left(\frac{kg}{MW^2}\right)$	2	3.82	5.01	1.1	3.55
$e_i\left(\frac{kg}{MW}\right)$	-5	-4.24	-2.15	-3.99	-6.88
$e_i(kg)$	3	6.09	5.69	6.2	5.57
Pmin (MW)	28	90	68	76	19
Pmax (MW)	206	284	189	266	53

4.2 Case 1: Economic Dispatch

In this case, the objective is to minimize the total fuel cost while satisfying generator limits and power demand.

The generator outputs obtained using the base method and PSO are almost identical. The base method produces a total generation cost of 131455 \$/hr with an emission level of 96450.75. When PSO is applied, the total cost slightly decreases to 131454.36 \$/hr, while the emission becomes 96450.43. This result indicates that PSO is capable of finding a slightly better economic solution while maintaining similar generator scheduling patterns.

4.3 Case 2: Emission Dispatch

In emission dispatch, the objective is to minimize the total emission produced by the generating units. The base method achieves an emission level of 87089.40 with a corresponding cost of 148684.72 \$/hr. Using PSO, the emission slightly reduces to 87089.12, while the generation cost becomes 148686.05 \$/hr. The results show that PSO is effective in minimizing emissions, although a slight increase in cost is observed due to prioritizing cleaner generator operation.

4.4 Case 3: Penalty Method

The penalty method combines fuel cost and emission into a single objective function. Using the base method, the obtained cost is 131552.14 \$/hr with an emission of 94428.55. When PSO is applied, the cost slightly reduces to 131551.61 \$/hr, and the emission becomes 94427.12. These results demonstrate that PSO can provide a better compromise solution between economic and environmental objectives.

4.5 Case 4: Emission Constrained Dispatch

In this case, the emission level is restricted to 90000 units while minimizing the fuel cost. Both methods satisfy the emission constraint exactly. The base method produces a cost of 133190.13 \$/hr, whereas PSO slightly improves the result with a cost of 133189.13 \$/hr. This shows that PSO can maintain environmental constraints while achieving marginally improved economic performance.

4.6 Case 5: Pareto Front Generation

In this case, a multi-objective optimization approach is used to analyse the trade-off between fuel cost and emission. Table 4 presents the Pareto optimal solutions obtained using the base method and the PSO algorithm. The results show that reducing emission increases the generation cost, demonstrating the conflicting nature of economic and environmental objectives. The emission values vary from 96444 to 87089, while the corresponding cost ranges from 131460 \$/hr to 148690 \$/hr. The PSO-based Pareto solutions provide a smoother distribution of trade-off points, indicating better exploration of the solution space.

4.7 Case 6: Load Variation Study

In this case, the system performance is analysed under different load demands of 400 MW, 450 MW, 500 MW, and 550 MW. Table 5 presents the optimal generator outputs, total generation cost, and emission levels obtained using the base method and the PSO algorithm.

The table 5 results show that both generation cost and emission increase with increasing load demand, which is expected due to higher generator output requirements. The generator outputs obtained from both methods are very close for all load levels. However, the PSO algorithm consistently provides slightly lower generation cost values, demonstrating its effectiveness in solving the Economic–Environmental Dispatch problem under varying load conditions.

This figure 1 shows the trade-off relationship between generation cost and emission for the Base Method and PSO. The PSO curve provides slightly improved optimal solutions, achieving lower cost for similar emission levels compared to the Base Method.

Table 3: Comparative Results of Base and PSO for Case 1 to Case 4

Case	Method	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	Total Cost ($/hr)	Total Emission (kg)
Case 1 Economic Dispatch	Base	102.8442	90	76.7303	77.4255	53	131455	96450.75
	PSO	102.8406	90	76.7326	77.4259	53	131454.4	96451.08
Case 2 Emission Dispatch	Base	71.622	90	68	129.7628	40.6152	148684.7	87089.4
	PSO	71.6244	90	68	129.7593	40.6153	148682.2	87089.12
Case 3 Penalty Method	Base	103.2595	90	73.0637	80.6768	53	131552.1	94428.55
	PSO	103.2588	90	73.0572	80.683	53	131551.9	94424.59
Case 4 Emission Constrained	Base	94.2115	90	68	94.7885	53	133190.1	90000
	PSO	94.2127	90	68	94.7863	53	133189.1	90000

Table 4: Pareto Optimal Solutions for Cost–Emission Trade-off (Base Method vs PSO)

Point	Base Cost ($/hr)	Base Emission (kg)	PSO Cost ($/hr)	PSO Emission (kg)
1	148680	87089	148690	87089
2	138030	88026	141720	87431
3	134910	88962	137340	88187
4	133310	89898	134870	88977
5	132460	90834	133730	89585
6	132040	91770	132980	90195
7	131810	92706	132490	90786
8	131650	93642	132190	91350
9	131540	94578	131950	92117
10	131470	95515	131570	94231
11	131460	96444	131450	96451

Table 5: Load Variation Study: Comparison of Base Method and PSO Results

Load (MW)	Method	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	Total Cost ($/hr)	Total Emission (kg)
400	Base	102.844	90	76.7303	77.4255	53	131455	96450.75
	PSO	102.844	90	76.7301	77.4241	53	131454.4	96450.6
450	Base	122.508	90.985	91.2962	92.2104	53	166312.1	120822.3
	PSO	122.508	90.986	91.29	92.2144	53	166311.3	120818.3
500	Base	137.972	102.439	102.7509	103.8373	53	206384.1	150788.4
	PSO	137.974	102.443	102.7428	103.8381	53	206383.2	150784.6
550	Base	153.435	113.894	114.2055	115.4643	53	251095.3	184325.6
	PSO	153.433	113.900	114.2027	115.4623	53	251094.3	184325.6

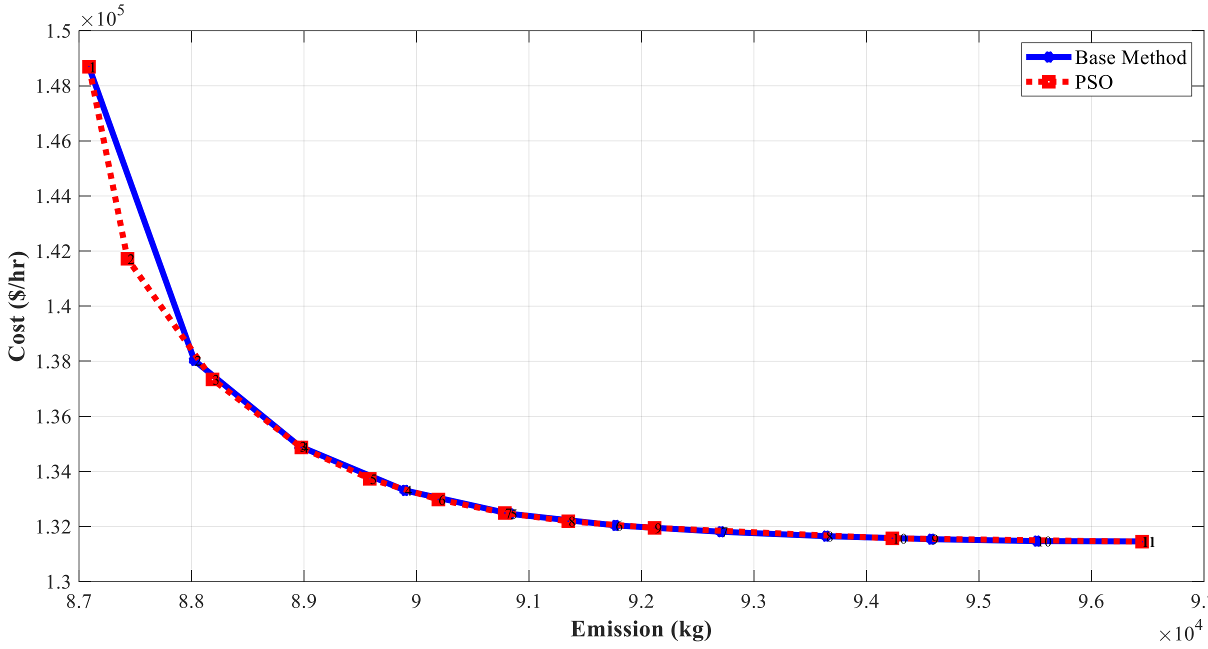

Figure 1. Cost–Emission Pareto Curve Comparison

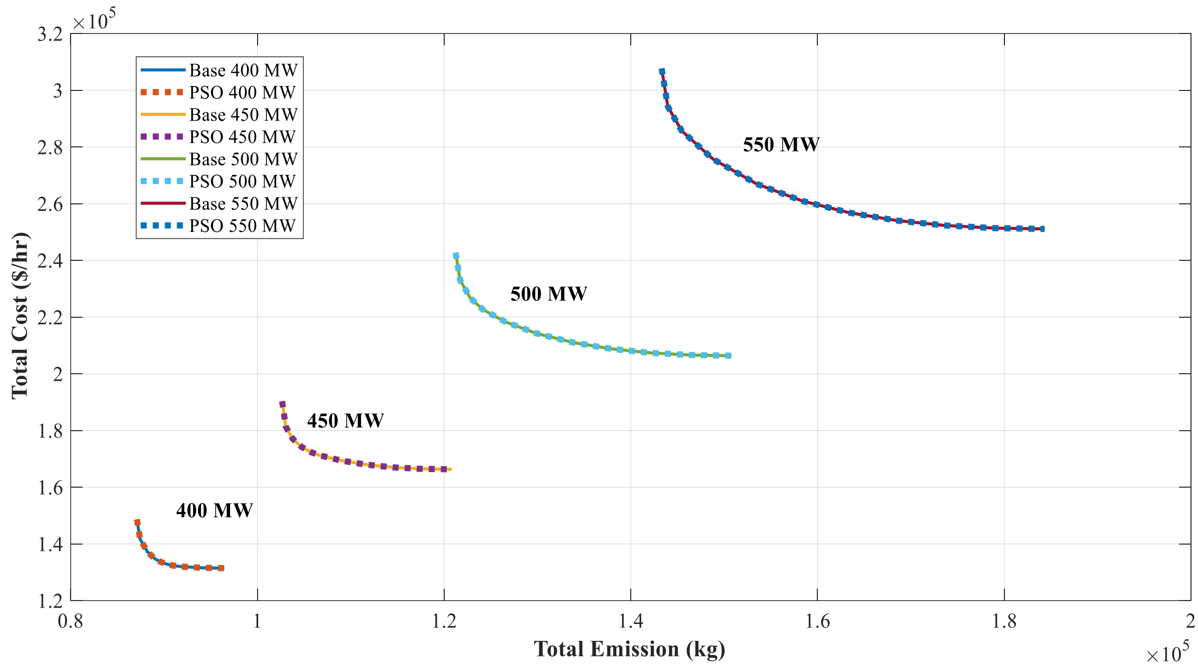

Figure 2: Pareto Front Comparison of Base Method and PSO for Different Load Demands

This figure 2 illustrates the Pareto front representing the trade-off between total generation cost and emission for different load demands (400 MW, 450 MW, 500 MW, and 550 MW). Both the Base optimization method and Particle Swarm Optimization (PSO) are compared to obtain optimal operating points. Each curve shows the set of feasible solutions balancing economic and environmental objectives. The results demonstrate that PSO provides slightly improved or comparable solutions across the load conditions.

This study investigates the EED problem for a five-generator thermal power system to minimize fuel cost and emission while satisfying generator limits and power demand. Six cases are analysed: economic dispatch, emission dispatch, penalty-based optimization, emission-constrained dispatch, Pareto front generation, and load variation analysis. These scenarios evaluate system performance under different objectives and constraints. The results show that the PSO algorithm provides slightly improved or comparable solutions compared to the base optimization method, demonstrating its effectiveness for solving EED problems under various operating conditions.

5. CONCLUSION

This study investigated the Economic–Environmental Dispatch (EED) problem for a five-generator thermal power system using Particle Swarm Optimization (PSO). Six case studies were analysed, including economic dispatch, emission dispatch, penalty-based dispatch, emission-constrained dispatch, Pareto front generation, and load variation analysis. For the 400 MW demand, PSO slightly reduced the generation cost from 131455 \$/hr to 131454.36 \$/hr (≈0.0005%) in economic dispatch. In emission dispatch, the emission was marginally reduced from 87089.40 to 87089.12 (≈0.0003%). In the penalty-based and emission-constrained cases, PSO achieved small improvements while satisfying system constraints. The Pareto analysis showed the trade-off between cost (131460–148690 \$/hr) and emission (87089–96444). The load variation study indicated that cost increased from 131455 \$/hr to 251095 \$/hr as the demand increased from 400 MW to 550 MW. Overall, PSO demonstrated stable performance and slightly improved solutions across all scenarios, confirming its effectiveness for solving Economic–Environmental Dispatch problems.

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