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A Hybrid PSO–ANN Approach for Economic Load Dispatch of a Thermal Power System Considering Transmission Losses

Mr. Vinod Chouhan[1], **Mr. Lokesh Patidar**[2]

[1]*M. Tech Scholar in Power Electronics, JIT, Borawan (M.P). E-mail: (vinchouhan0805@gmail.com)*

[2]*Assistant Professor & head in Electrical & Electronics Dept. JIT, Borawan (M.P). E-mail: (er.lavkesh27@gmail.com)*

Abstract: Economic Load Dispatch (ELD) is a key operational task in power systems, aimed at meeting load demand at the minimum possible generation cost while strictly satisfying generator operating limits and system constraints. However, practical ELD problems are inherently non-linear and constrained, and the inclusion of transmission losses further increases their complexity, making conventional optimisation techniques less effective. To address these challenges, this work presents a hybrid optimisation framework that combines Particle Swarm Optimization (PSO) with an Artificial Neural Network (ANN) for solving the ELD problem of a three-generator thermal power system, explicitly considering transmission losses.

In the proposed approach, the ELD problem is formulated using quadratic fuel cost functions, generator capacity limits, and transmission losses represented through the B-coefficient method. PSO is first applied to determine high-quality optimal dispatch solutions due to its strong global search capability and reliable convergence behaviour. The optimal solutions obtained from PSO are then utilised to train an ANN, enabling it to learn the non-linear relationship between system load demand and corresponding generator power outputs.

Keywords: Economic Load Dispatch; Particle Swarm Optimization; Artificial Neural Network; Hybrid PSO–ANN; Transmission Losses; Power System Optimisation

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I. INTRODUCTION

Economic Load Dispatch (ELD) is a fundamental optimisation problem in power system operation, focused on supplying the required load demand at the lowest possible generation cost while satisfying operational and system constraints. In practical power systems, the ELD problem becomes highly non-linear due to generator characteristics, operating limits, and the presence of transmission losses. These factors often limit the effectiveness of conventional optimisation methods. To overcome these limitations, this study proposes a hybrid solution methodology that integrates Particle Swarm Optimization (PSO) with an Artificial Neural Network (ANN) for efficient and accurate ELD analysis.

In this work, the ELD formulation incorporates quadratic fuel cost functions, generator minimum and maximum power limits, and transmission losses modelled using the B-coefficient approach. PSO is initially employed to compute optimal generator dispatch solutions because of its strong global search capability and consistent convergence behaviour. The optimal solutions obtained from PSO are treated as reference data and used to train an ANN, enabling it to capture the complex and non-linear relationship between load demand and generator power outputs.

MATLAB-based simulations demonstrate that the PSO algorithm yields feasible and accurate dispatch solutions with minimal power mismatch. The ANN-based approach produces dispatch results that closely match the PSO benchmarks in terms of generator outputs and total generation cost, with only slight deviations observed. Moreover, the ANN significantly reduces computational effort, making the proposed hybrid PSO–ANN framework well suited for fast and near real-time Economic Load Dispatch applications in modern power systems.

II. LITERATURE REVIEW

2.1 Evolution of Economic Load Dispatch Research

Research on Economic Load Dispatch (ELD) has progressed alongside the expansion of power systems and the growing emphasis on cost-effective and reliable operation. Early ELD studies were mainly concerned with reducing the operating cost of thermal power plants and were based on simplified assumptions such as smooth fuel cost curves, negligible transmission losses, and a small number of generators.

As power systems became larger and more interconnected, researchers began incorporating practical factors such as generator operating limits and transmission losses into ELD formulations. While this improved modelling accuracy, it also introduced strong non-linearity and increased computational complexity, exposing the limitations of classical analytical methods. To address these challenges, numerical and heuristic-based approaches were later explored, offering better flexibility and improved handling of complex constraints, although issues related to computational effort and scalability remained.

In recent years, ELD research has shifted towards achieving high solution accuracy, faster computation, and adaptability to varying operating conditions. Modern approaches focus not only on cost minimisation but also on feasibility, robustness, and suitability for online or near real-time applications. This evolution reflects the changing requirements of contemporary power systems and provides a basis for advanced dispatch strategies discussed in later works.

Table 1 Evolution of Economic Load Dispatch Research

Research Phase	Key Characteristics	Major Limitations
Early analytical methods	Incremental cost-based, simplified assumptions	Limited to small systems, convex cost functions
Loss-inclusive formulations	Consideration of transmission losses	Increased non-linearity and computational complexity
Numerical and heuristic era	Improved robustness and constraint handling	Higher computation time for large systems
Modern approaches	Focus on accuracy, feasibility, and speed	Need for balanced optimisation frameworks

2.2 Generator Cost Modeling and Characteristics

Accurate representation of generator fuel cost characteristics is essential for effective Economic Load Dispatch (ELD) analysis, as fuel cost directly reflects the expense of power generation and is influenced by factors such as fuel type, efficiency, and operating conditions. Proper cost modelling enables realistic estimation of operating costs and has a direct impact on the quality of dispatch decisions.

In early ELD studies, generator fuel costs were typically modelled using smooth quadratic functions, assuming a continuous and convex relationship between cost and power output. This simplified formulation allowed analytical optimisation and provided a reasonable approximation of thermal generator behaviour across normal operating ranges. Along with cost modelling, practical operating constraints such as minimum and maximum generation limits are incorporated to ensure safe and feasible operation.

Incremental fuel cost concepts have traditionally been used to determine optimal load sharing among generators, with classical dispatch theory scheduling units such that incremental costs are equal at the optimum point. However, real-world generator characteristics often deviate from smooth behaviour due to effects such as valve-point loading and multiple fuel options.

Table 2 Common Generator Cost Models Used in ELD Studies

Cost Model Type	Mathematical Representation	Key Features	Limitations
Quadratic cost model	Second-order polynomial	Simple, convex, analytically tractable	Does not capture non-smooth behaviour
Incremental cost model	First derivative of the cost function	Useful for load-sharing analysis	Limited applicability under non-linearity
Non-smooth cost model	Quadratic with sinusoidal components	Represents valve-point effects	Increases optimisation complexity
Multi-fuel cost model	Piecewise cost functions	Models fuel switching behaviour	Difficult constraint handling

2.3 Constraint Handling in Economic Load Dispatch Problems

Constraint handling is a vital component of the Economic Load Dispatch (ELD) problem because real-world power system operation is subject to several physical and operational limitations. An effective ELD solution must minimise generation cost while simultaneously satisfying all equality and inequality constraints to ensure secure and reliable operation. Ignoring or improperly treating these constraints can lead to infeasible dispatch solutions that are not practically implementable.

The most important equality constraint in ELD is the power balance requirement, which ensures that total generated power matches system load demand along with transmission losses. This balance is essential for maintaining system frequency and overall stability. Any mismatch between generation and demand may result in frequency deviations and operational issues.

Beyond basic capacity limits, practical systems impose additional constraints such as ramp-rate limits and prohibited operating zones. Ramp-rate limits restrict how quickly generator output can change, while prohibited zones prevent operation in ranges that may cause mechanical stress or thermal issues. Although these constraints improve modelling realism, they also increase the non-linearity and complexity of the ELD problem.

2.4 Research Gaps

The literature surveyed in this chapter demonstrates the steady evolution of Economic Load Dispatch (ELD) research, progressing from classical analytical models to more advanced techniques focused on improving practical accuracy and computational performance. Existing studies have laid a strong foundation by examining generator cost characteristics, constraint management, and the impact of transmission losses on dispatch outcomes.

The review further reveals that effective treatment of transmission losses and operational constraints remains a major challenge. Although many approaches account for losses, the resulting non-linearity significantly increases solution complexity and often affects convergence reliability. In addition, ensuring feasible dispatch solutions throughout the optimisation process is still problematic, particularly when approximation or data-driven methods are applied.

Table 3 Summary of Literature Findings and Identified Research Gaps

Literature Observation	Identified Research Gap
Reliance on simplified cost and loss models	Need for realistic and loss-sensitive ELD formulation
High computational effort of accurate methods	Requirement for faster dispatch solutions
Difficulty in handling complex constraints	Need for robust feasibility-preserving strategies
Trade-off between accuracy and speed	Scope for integrated optimisation and estimation approach

The identification of these research gaps provides a clear motivation for the work presented in this work. The subsequent chapter focuses on the formal formulation of the ELD problem and the identification of practical challenges, which form the basis for the proposed solution framework.

III. ECONOMIC LEAD DISPATCH:CONCEPT

Economic Load Dispatch (ELD) represents a core optimisation task in power system operation, concerned with distributing the total load demand among available generating units in a manner that minimises overall fuel cost while respecting all operational constraints. The formulation generally assumes steady-state operating conditions and adequate generation capacity to meet the system demand. Under these assumptions, ELD serves as a key decision-making tool for economical system operation.

In practical power systems, multiple generators operate simultaneously, each characterised by distinct fuel cost curves influenced by fuel type, efficiency, and operating conditions. The objective of ELD is to allocate generation such that units with lower incremental costs supply a larger share of the demand, while higher-cost units operate at reduced output levels, within their permissible limits. This coordinated allocation ensures cost-effective operation without compromising system reliability.

From a mathematical perspective, ELD is modelled as a constrained optimisation problem in which the total generation cost, typically expressed as a quadratic function of generator output, is minimised. The optimisation is subject to an equality constraint enforcing power balance, where total generation must match load demand along with transmission losses, and inequality constraints representing generator capacity limits. The inclusion of these constraints introduces non-linearity and, in certain cases, non-convexity into the problem.

IV. HYBRID PSO-ANN FRAMEWORK

The hybrid PSO–ANN approach integrates the strong optimisation capability of Particle Swarm Optimization with the rapid estimation performance of Artificial Neural Networks to provide an efficient solution for the Economic Load Dispatch problem. This hybridisation is motivated by the need to utilise the complementary advantages of both methods while overcoming their individual shortcomings.

Subsequently, an ANN is trained using the PSO-derived optimal dispatch results. Through supervised learning, the ANN learns the non-linear mapping between system load demand and the corresponding optimal generator outputs. After training, the ANN acts as a fast estimator, capable of producing near-optimal dispatch solutions with substantially lower computational effort than iterative optimisation techniques.

The operation of the hybrid framework is organised into two main stages: a training phase and a deployment phase. In the training phase, PSO is executed across multiple load levels to form a representative dataset of optimal dispatch patterns. During deployment, the trained ANN predicts generator outputs for a given load demand, followed by a correction process to ensure compliance with power balance and transmission loss constraints.

Mathematically, the hybrid framework can be expressed as a two-stage mapping:

PSO stage: $P^* = \arg\min F(P)$ subject to system constraints

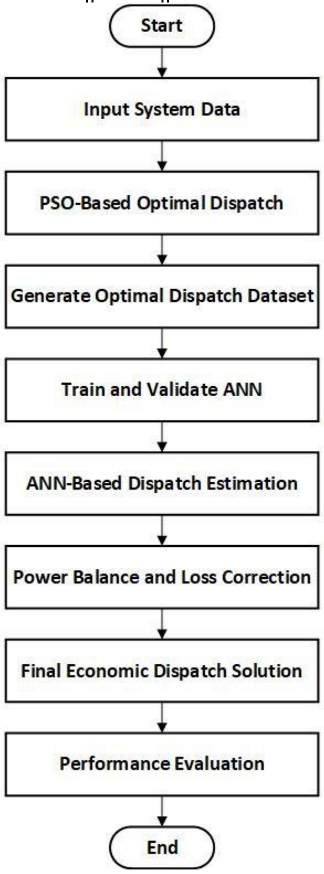
$$\text{ANN stage: } P_{ANN} \approx f(P\_D)$$

Where, P^* denotes the PSO-optimised generator outputs, $F(P)$ is the ELD objective function, f(.) represents the learned ANN mapping, P_D is the system load demand.

The feasibility of ANN-estimated outputs is ensured using the correction strategy discussed in Chapter 3, which adjusts generator outputs to satisfy the power balance equation with transmission losses. This ensures that the speed advantage of ANN does not compromise physical feasibility. The hybrid PSO–ANN framework offers a balanced solution for ELD by combining optimisation accuracy with computational efficiency. It is particularly suitable for applications where dispatch decisions must be obtained quickly without sacrificing economic performance. The next work details the complete implementation procedure and algorithmic steps followed in this study.

4.1 Algorithmic Implementation Procedure

These parameters define the ELD problem formulation and remain fixed during optimisation. The PSO algorithm is executed for predefined load demand levels. Transmission losses are calculated using the B-coefficient method, and power balance is enforced. The optimal dispatch solutions obtained from PSO are arranged as input–output pairs for ANN training. A feedforward ANN is trained using the prepared dataset.



The trained ANN is employed to estimate generator outputs for new or unseen load demand values, enabling fast dispatch estimation without iterative optimisation. The ANN-estimated generator outputs are adjusted to satisfy generator limits and the power balance equality constraint, including transmission losses. The final dispatch results are evaluated by comparing ANN-based solutions with PSO-based optimal solutions using metrics.

V. RESULTS AND DISCUSSIONS

At the beginning of the simulation study, a standard three-generator thermal power system is considered to analyse the performance of the proposed Economic Load Dispatch techniques. The total system load demand is taken as 300 MW, and all generators are scheduled to operate within their prescribed operating limits. Generator 1 operates between 50 MW and 200 MW, Generator 2 between 50 MW and 150 MW, and Generator 3 between 50 MW and 100 MW. Each generating unit is modelled using a quadratic fuel cost function of the form ($C_i(P_i) = a_i P_i^2 + b_i P_i + c_i$), with cost coefficients selected from commonly used benchmark data reported in the literature. Transmission losses are explicitly considered using the B-coefficient loss model, where the loss coefficients matrix is defined as

$$B = \begin{bmatrix} 0.0002 & 0.00001 & 0.000015 \\ 0.00001 & 0.00025 & 0.00002 \\ 0.000015 & 0.00002 & 0.0003 \end{bmatrix}$$

The same generator data, load demand, and loss coefficients are used for both PSO-based optimisation and ANN-based dispatch estimation to ensure a fair and consistent comparison of results. The total generation obtained in all cases satisfies the load demand after accounting for transmission losses, thereby validating the feasibility of the dispatch solutions.

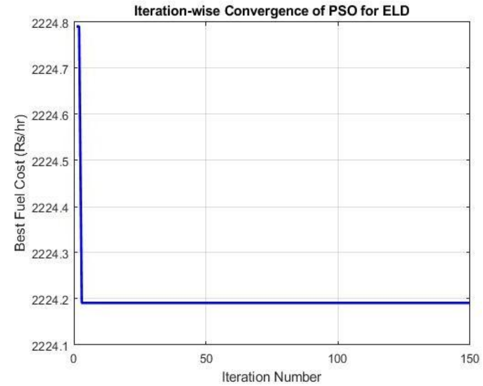


Figure 2: Iteration-wise convergence of the best fuel cost obtained using PSO

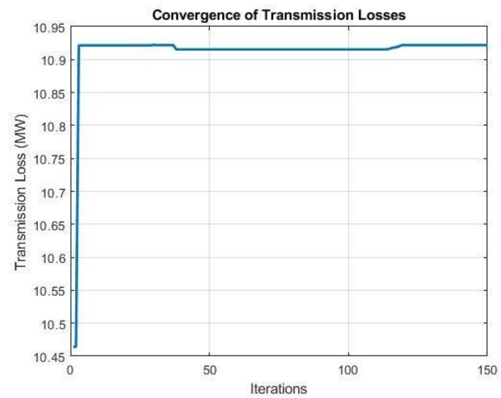


Figure 3: Convergence behaviour of transmission losses during PSO iterations

The PSO algorithm demonstrates strong performance in solving the ELD problem, particularly in terms of convergence reliability and solution quality. Its ability to handle non-linear cost functions and transmission losses without requiring gradient information makes it well suited for practical dispatch problems.

However, it is observed that PSO requires a relatively higher computation time compared to direct estimation methods, especially when multiple load scenarios are considered. This limitation motivates the integration of PSO with ANN-based estimation to achieve faster dispatch solutions, which is explored in the subsequent works of this chapter.

This work presents the results obtained using the Artificial Neural Network (ANN) for estimating generator dispatch in the Economic Load Dispatch (ELD) problem. The ANN is trained using optimal dispatch solutions generated by the Particle Swarm Optimization (PSO) algorithm under varying load demand conditions.

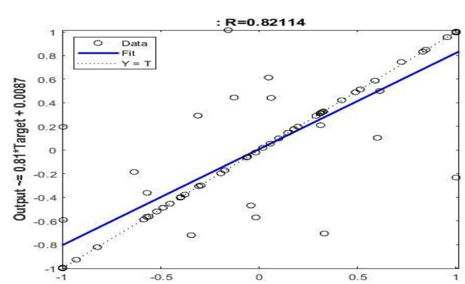


Figure 4 Regression analysis between PSO target outputs and ANN-estimated outputs

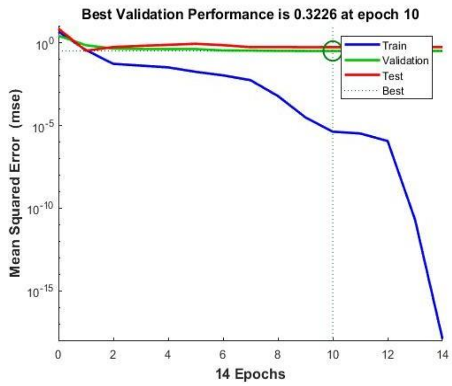


Figure 5 Training, validation, and testing performance curve of the ANN

While the ANN demonstrates strong estimation accuracy and computational speed, it is inherently dependent on the quality and diversity of training data. Since the ANN is trained using PSO-generated solutions, its performance reflects the optimisation quality achieved by PSO. As a result, the ANN should not be viewed as a standalone optimiser but rather as a fast estimator that complements optimisation-based approaches.

These observations motivate the adoption of a hybrid PSO–ANN framework, where PSO ensures optimality, and ANN provides rapid dispatch estimation.

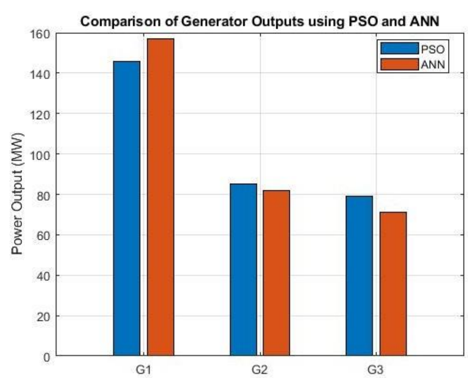


Figure 6 Comparison of generator power outputs obtained using PSO and ANN.

This bar chart compares the individual generator power outputs obtained using PSO and ANN-based approaches. The close alignment of the bars confirms that the ANN successfully captures the dispatch pattern of the PSO-based optimal solution.

VI. CONCLUSION

This work has presented a detailed investigation of the Economic Load Dispatch (ELD) problem for a thermal power system while explicitly accounting for transmission losses, with the aim of achieving economical and feasible generation scheduling. The study progressed in a structured manner, starting from problem formulation and literature review, and culminating in the development and assessment of a hybrid optimisation framework based on Particle Swarm Optimization (PSO) and Artificial Neural Networks (ANN).

The ELD problem was initially formulated by incorporating realistic system characteristics such as quadratic fuel cost functions, generator operating constraints, and transmission losses modelled using B-coefficients. This formulation clearly demonstrated the non-linear and constrained nature of the problem, justifying the need for robust optimisation techniques. PSO was subsequently employed to obtain optimal dispatch solutions, showing consistent convergence and the ability to minimise generation cost while satisfying power balance requirements.

An ANN-based dispatch estimator was then developed using PSO-generated optimal solutions as training data. The trained ANN effectively captured the non-linear relationship between load demand and generator outputs, enabling fast dispatch estimation for unseen operating conditions. Although small deviations from PSO solutions were observed due to the approximate nature of ANN predictions, the application of power balance and loss correction ensured that all results remained feasible and practically acceptable.

Comparative analysis between PSO and the hybrid PSO–ANN framework demonstrated that the hybrid approach achieves near-optimal economic performance with a substantial reduction in computational time.

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