

Hybrid RSM–RFR Approach for Economic Load Dispatch of a Thermal Power System Considering Transmission Losses

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Abstract - Economic Load Dispatch (ELD) plays an important role in power system operation by determining an economical generation schedule while satisfying load demand and generator operating constraints. The inclusion of transmission losses and nonlinear fuel cost characteristics makes the dispatch problem more challenging. This study presents a hybrid Response Surface Methodology–Random Forest Regression (RSM–RFR) framework for ELD of a three-generator thermal power system considering transmission losses. The system operates at a total load demand of 300 MW, with generator limits of 50–200 MW, 50–150 MW, and 50–100 MW, respectively. Quadratic fuel cost functions are used to represent generation costs, while transmission losses are calculated using the B-coefficient method. RSM is employed to identify an economical dispatch schedule by minimizing the total fuel cost under the specified operating constraints. The optimized solutions are subsequently used to train an RFR model for rapid prediction of generator outputs under varying load conditions. The predicted schedules are further adjusted to satisfy generator limits and the power-balance constraint, including transmission losses. Model performance is evaluated using the coefficient of determination (R^2), total fuel cost, transmission losses, and convergence characteristics. The results indicate that the proposed RSM–RFR approach can provide near-optimal dispatch solutions with lower computational effort and reliable predictive performance. The developed framework therefore offers a practical data-driven approach for economical operation of thermal power systems.

Key Words : Economic Load Dispatch; Response Surface Methodology; Random Forest Regression; Fuel Cost Optimization; Generator Scheduling; Power System Optimization

1.INTRODUCTION

One of the most important optimization problems in the operation of power systems is Economic Load Dispatch (ELD), the main target of which is the provision of the necessary load demand of the system at the lowest possible fuel consumption,

ensuring the secure, reliable, and stable operation of the system [1-5]. In thermal power plants, fuel cost makes up the biggest fraction of all operating costs; therefore, correct scheduling of generating units becomes paramount in increasing economic efficiency, reliability in operating, and stability of the whole system.

An ELD problem is typically presented as a constrained optimization problem where the overall fuel cost of committed generating units is minimized and equality and inequality constraints are met. The equality constraint is applied to ensure that the system load demand plus the transmission losses should be equal to the amount of power supplied, and the inequality constraints are applied in order to set restrictions on how the generators can operate, such as ramp-rate restrictions and prohibited operating regions [6-9]. In real-world power systems, the presence of valve-point loading effects, non-smooth fuel cost behavior, multiple fuel selections, and transmission losses causes the ELD problem to be very non-linear and non-convex. The complications lower the efficiency of the traditional algorithms like Lambda iteration, dynamic programming, and gradient based optimization algorithms.

In order to address such shortcomings, various enhanced optimization tools like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Artificial Bee Colony (ABC), Evolutionary Programming (EP) and other hybrid metaheuristic algorithms have been extensively used to solve ELD problems [10-15]. These optimization techniques provide superior global search functionalities, superior convergence features and superior reaction to realistic dispatch constraints in comparison to conventional analytical instruments. According to many researchers, the metaheuristic strategies are more effective in minimizing fuel costs and generating more precise scheduling of the generators in complicated dispatch systems.

More recent shifts in the modern power system, such as incorporation of renewable energy, electric vehicles, windsolar systems, microgrids, and low-carbon dispatch strategies have further complicated the Economic Load Dispatch analysis. These new energy systems demand optimization methods that

do not only offer correct dispatching solutions but also assist quicker prediction and real-time operational choice processes. This leads to a high demand of integrating the optimization techniques with machine learning-based predictive models to get economical and practical dispatch solutions.

A new benchmark study examined the ELD issue of a typical three-generator thermal power system with transmission losses with the help of a hybrid PSO-ANN structure. The work assumed a total load demand of 300 MW with Generator 1 and Generator 2 varying between 50-200 MW and 50-150 MW, respectively, and Generator 3 varying between 50-100 MW as well. A quadratic fuel cost model was used to model each generating unit and transmission losses were modeled using the B-coefficient method. The optimum dispatch solution was determined using Particle Swarm Optimization and the outputs of the generators were quickly estimated using Artificial Neural Network.

Although the PSO-ANN framework demonstrated strong optimization capability and reduced computational effort, ANN performance depends heavily on the quality of training data and repeated parameter tuning. In addition, prediction inconsistency may occur for unseen load demand conditions, which may reduce dispatch reliability and practical implementation efficiency.

Response Surface Methodology (RSM) is a powerful statistical optimization technique which is used to represent mathematical models between input variables and responses. It is useful in determining the best operating conditions, interaction of factors and minimizing computational complexity. Random Forest Regression (RFR) is a machine learning prediction algorithm that is described by high prediction accuracy, robustness and high capacity to handle complex non-linear problems in engineering. Therefore, the present work proposes a hybrid RSM-RFR approach for solving the Economic Load Dispatch problem of a three-generator thermal power system considering transmission losses. The same benchmark generator data, fuel cost functions, generator operating limits, and B-coefficient loss model used in the reference PSO-ANN study are adopted to maintain consistency and ensure fair comparison.

RSM is employed in the proposed framework to optimize total fuel costs minimization and RFR is employed to predict and validate optimal dispatch solutions. The suggested solution will enhance optimization effectiveness, forecasting accuracy, and pragmatism of the current thermal power systems operation.

2. Literature Review

Economic Load Dispatch (ELD) studies have evolved alongside the expansion of the contemporary power framework and the rise in the need to have cost-effective, trustworthy and efficient electricity production. The main aim of ELD is to reduce the overall cost of generation of fuel and meet the load requirement of the system and be able to meet all operational constraints of generating units. During the initial phase of ELD development, research was predominantly on simplified thermal power systems whose fuel costs are simple, their transmission losses are insignificant and, there are few generating units. These traditional methods mostly relied on incremental cost, Lambda Iteration and Dynamic Programming techniques, which were applicable to small systems only having convex cost functions [16-18].

With the increase in size and interconnection of power systems, the practical limits of operating generators, transmission losses, forbidden operating zones, ramp-rate limitations, and loading

effects of a valve-point became part of ELD formulations. These considerations enhanced the reality of the model, but also created a high degree of non-linearity and non-convexity making the problem harder to solve with traditional analytical optimization techniques [19-21].

To overcome these limitations, different heuristic and metaheuristic optimization methods such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Evolutionary Programming (EP), Differential Evolution (DE) and Artificial Bee Colony (ABC) have been widely used to solve ELD problems. [22-26]. These methods offer enhanced global search, enhanced convergence properties and enhance practical dispatch constraints than the conventional mathematical methods.

Genetic Algorithm has been extensively used in the resolution of Economic Load Dispatch problems where valve-point loading is involved as well as realistic operating constraints. GA has been claimed to be capable of global optimization over local minima, and more convergence-friendly than conventional optimization algorithms. [8,9]. Experiments with large scale ELD systems and line flow constraints also demonstrated that GA can be used to deal with realistic system constraints economically and with less computational effort [9,10].

Genetic Algorithm that is coded in real code has also been effectively used in combined economic emission dispatch with better parameter tuning and performance in optimization [11]. Similarly, Artificial Bee Colony algorithm has been used in dynamic economic dispatch with valve-point effects which result in improved constraint management and fuel savings [12]. Multi-objective Differential Evolution has been shown to exhibit good trade-offs in environmental dispatch issues in economics and minimization of emissions [13].

Adaptive Hopfield Neural Networks have been used on ELD and it is reported to be faster in estimating dispatches with acceptable solution accuracy [14]. Non-smooth fuel cost problems have also been solved with the use of Evolutionary Programming and demonstrated the ability to effectively address the complexity of generator scheduling and converge reliably with constrained dispatch conditions [15,16].

Recent ELD research has been on hybrid optimization strategies that include integration of renewable energy, electric vehicles, microgrids, wind-integrated and low-carbon dispatch strategies. Hybrid Jaya Optimization combined with Genetic Algorithm has shown improved convergence stability and better fuel cost minimization for large-scale ELD problems [17]. Hybrid optimization techniques have also allowed optimization of the grid flexibility and sustainable energy management due to the integration of electric vehicles and renewable sources of energy. [18]. Renewable generation combined with load forecasting has improved dispatch efficiency and operational planning [19], while fractional hybrid optimization strategies for wind-integrated systems have achieved reliable and cost-effective dispatch solutions under renewable uncertainty [20].

A benchmark study presented a hybrid PSO-ANN framework for solving the ELD problem of a standard three-generator thermal power system considering transmission losses [21]. In that work, Particle Swarm Optimization was used to obtain optimal dispatch solutions, while Artificial Neural Network was trained using PSO-generated results for fast prediction of generator outputs. The study showed that ANN-based predictions closely matched PSO benchmark solutions with significantly reduced computational effort. However, ANN performance remained strongly dependent on training quality

and repeated parameter tuning, which may affect prediction consistency for unseen load demand conditions.

Engineering optimization has also widely used Response Surface Methodology (RSM) to create mathematical models between variables of interest and output response and reduce the number of computations. . It helps in identifying optimal operating conditions and understanding factor interactions [22,23]. Random Forest Regression (RFR) is a robust machine learning regression framework, which is defined by high prediction accuracy, non-linear learning and good performance with complicated engineering systems [24-26].

The combination of RSM and RFR offers an efficient hybrid structure to optimize and predict Economic Load Dispatch issues. RSM provides systematic optimization of minimization of total fuel cost, whereas RFR offers quick and precise prediction of generator outputs to different load demand conditions. Therefore, the present study extends the benchmark PSO-ANN framework by replacing PSO with RSM and ANN with RFR for solving the ELD problem of a three-generator thermal power system considering transmission losses.

The objective of this approach is to enhance optimization efficiency, prediction capability and workability of thermal power systems in the present day.

Table -1: Development Trends in Economic Load Dispatch Optimization Techniques

Development Stage	Main Approach	Major Drawbacks
Classical Dispatch Methods	Incremental cost and lambda-based analytical methods	Suitable only for simple convex systems
Loss-Aware Dispatch Models	Inclusion of transmission loss effects	Higher mathematical complexity
Metaheuristic Optimization Stage	GA, PSO, EP, ABC-based optimization methods	Increased computational time
Hybrid Intelligent Models	Optimization + prediction-based approaches	Need for better balance between speed and accuracy

Table 1 illustrates the development of Economic Load Dispatch research from classical analytical methods to modern hybrid optimization techniques. At first the ELD problems were addressed by incremental cost-based approaches that only apply to small and convex systems. Subsequently, the addition of transmission losses and realistic generator limitations complicated systems, prompting to heuristic and metaheuristic optimization methods. Recent strategies emphasize the need to achieve a balance between optimization accuracy, computation speed, and prediction ability, which is a powerful argument in favor of the development of the proposed hybrid RSM -RFR framework.

2.1 Generator Cost Modeling and Characteristics

Accurate representation of generator fuel cost characteristics is essential for effective Economic Load Dispatch analysis because fuel cost directly reflects the expense of power generation and is strongly influenced by fuel type, generator efficiency, heat rate, and operating conditions. Proper fuel cost modeling allows realism in estimating the operating costs and has a direct influence on dispatch quality, accuracy of optimization and feasibility of solutions. In the early development of ELD studies, generator fuel costs were commonly represented using smooth quadratic functions by assuming a continuous and convex relationship between generation cost and power output. This simplified formulation made analytical optimization possible and provided a practical approximation of thermal generator behavior under normal operating conditions The quadratic fuel cost model is the most used formulation in Economic Load Dispatch studies due to its simplicity, analytical tractability and mathematical stability. [27–30].

The normal quadratic fuel cost equation is normally presented as:

$$C_i(P_i) = a_i P_i^2 + b_i P_i + c_i$$

where C_i represents the total fuel cost of the i th generating unit, P_i is the generated power output, and a_i , b_i , and c_i are the fuel cost coefficients of every generator. This formulation is also adopted in the benchmark three-generator thermal power system used in the present study.

Incremental fuel cost concepts have traditionally been used for determining optimal load sharing among generating units The classical dispatch theory is based on the scheduling of generators so that incremental fuel costs equal at the optimal operating point. But in reality the characteristics of generators are not smooth quadratic because of practical considerations like valve-point loading, multiple fuel choices, and black-box operating limits.

To improve modeling realism, non-smooth cost models and multi-fuel cost functions are often introduced. Non-smooth cost models add sinusoidal terms to capture the effects of loading at valve points, and multi-fuel models add piecewise functions to capture the effects of fuel switching behavior.. Although these more complex models enhance real-world accuracy, and also add complexity and computation cost to optimization.

Hence, the quadratic fuel cost model remains the most popular benchmark model to most ELD studies due to its simple, accurate, and computationally efficient combination. Since the reference PSO-ANN benchmark study also uses the quadratic fuel cost model for the three-generator thermal power system, the same formulation is adopted in the present work to maintain consistency and ensure fair comparison.

Table -2: Generator Cost Function Models Used for Economic Dispatch Analysis

Cost Function Model	Functional Form	Advantages	Challenges
Quadratic Cost Function	Second-order polynomial	Simple and mathematically stable	Cannot represent valve-point effects
Incremental Cost Model	Derivative-based formulation	Useful for equal incremental dispatch	Less suitable for non-smooth systems
Valve-Point Cost Model	Quadratic + sinusoidal term	Represents practical generator behavior	Difficult optimization
Multi-Fuel Cost Model	Piecewise cost segments	Represents fuel switching operation	Complex constraint handling

Table 2 presents the major generator cost function models used in Economic Load Dispatch studies. The most used of these is the quadratic cost function due to its simplicity, convexity, and analytical quality. Since the benchmark reference paper also uses the quadratic fuel cost model for the three-generator thermal power system, the same model is adopted in the present study to maintain consistency and enable fair comparison.

2.2 Constraint Handling in Economic Load Dispatch Problems

The necessity of constraint management is one of the primary aspects of Economic Load Dispatch problem since the real-life functioning of power system is controlled by a number of physical, technical, and operational constraints. A good ELD solution should be able to reduce overall fuel production cost but at the same time meet all the equality and inequality constraints to achieve safe, stable and viable system operation. The dispatch solution may become infeasible when these constraints are not handled appropriately, and cannot be achieved in the actual power system. The power balance requirement is the most critical in ELD equality constraint that states that the amount of power generated should be equal to the sum of system load demand and transmission losses. This is a vital balance in determining system frequency stability, voltage stability, and the stability of operation as a whole. Any difference between the generation and use of power may lead to the frequency deviation, switching volatility and drastic interference of activity. Power balance equation. is expressed as:

$$P_1 + P_2 + P_3 = P_D + P_L$$

where P_1 , P_2 , and P_3 represent the generator outputs, P_D is the overall system load demand and P_L represents transmission losses. The B-coefficient loss model is usually used to compute the transmission losses and enhance the realism of

Economic Load Dispatch analysis. The transmission losses added to the problem of optimization make it more realistic, though also more difficult mathematically since it is non-linear. In addition to the equality constraint, we also have inequality constraints that define the permissible operating limits of each of the generators. They are minimum and maximum generation limits which make sure that every unit works in the safe and efficient range. The surpassing of any output of the generator above the limit may lead to mechanical stress, reduced efficiency, and hazardous working conditions.

Additional practical constraints such as ramp-rate limits and prohibited operating zones are also important in real-world dispatch problems. Ramp-rate limits put a limit on the rate at which the output of a generator can increase or decrease with time, and operating zones are prohibited even though they are in some unstable operating regimes because of vibration, thermal or mechanical reasons. Even though these practical constraints enhance the accuracy of the model and the reliability of the system, they greatly complicate the optimization process by making the ELD problem strongly non-linear and non-convex. Consequently, effective constraint management is critical in achieving realistically, cost-effective and practically viable dispatch solutions particularly when superior optimization and forecasting methods are used.

2.3 Research Gap

Most existing Economic Load Dispatch studies primarily focus either on achieving high optimization accuracy with increased computational effort or on using simplified mathematical models that reduce practical feasibility. Traditional optimization models like Lambda Iteration, Dynamic Programming and other analytical models can have problems in their ability to effectively deal with strong non-linearity, non-convex fuel cost properties and effects of transmission loss, particularly in a large-scale thermal power system [27-30]. Particle Swarm Optimization, Differential Evolution, Genetic Algorithm, and Artificial Bee Colony are metaheuristic optimization algorithms, which have significantly improved the performance of dispatch by improving the ability to global search and handling more constraints. However, they might be quite time-intensive to calculate, are repetitive, and are more complex when considering the many load demand cases. This is a big constraint to real-time operation of power systems where quick and dependable dispatching decisions are critical. The benchmark PSO-ANN framework improved prediction speed by combining optimization and machine learning for Economic Load Dispatch [21]. Although the approach demonstrated good optimization capability and reduced computational effort, the performance of Artificial Neural Network depends heavily on the quality of training data, repeated parameter tuning, and network architecture selection. Prediction inconsistency may also occur for unseen load demand conditions, which can reduce dispatch reliability and practical applicability.

In addition, very limited studies have focused on integrating statistical optimization techniques such as Response Surface Methodology (RSM) with robust machine learning regression methods like Random Forest Regression (RFR) for solving Economic Load Dispatch problems considering transmission losses. Majority of the current literature focuses on either optimization or prediction but not on coming up with a

balanced hybrid optimization-prediction model. Thus, there is an evident gap in research to create a realistic, computationally efficient and practically reliable hybrid methodology integrating systematic optimization with precise prediction ability. A combination of RSM and RFR provides a good chance to overcome these drawbacks by enhancing optimization performance, prediction quality and maintenance of feasibility of Economic Load Dispatch in thermal power plants.

Table -3: Summary of Literature Findings and Identified Research Gaps

Literature Observation	Research Gap Identified
Use of simplified cost and transmission loss models	Need for realistic and loss-sensitive ELD formulation
High computational effort of accurate optimization methods	Requirement for faster dispatch estimation
Difficulty in handling practical operating constraints	Need for robust feasibility-preserving strategies
Trade-off between optimization accuracy and computational speed	Scope for integrated optimization and prediction framework

Table 3 summarizes the major literature findings and corresponding research gaps identified from previous studies. The proposed hybrid RSM–RFR approach addresses these gaps by combining systematic optimization with robust machine learning-based prediction for improved Economic Load Dispatch performance.

2.4 Present Study

The present study focuses on Economic Load Dispatch of a standard three-generator thermal power system using a hybrid RSM–RFR approach for optimal generation cost minimization considering transmission losses.

The benchmark system is adopted from the reference PSO–ANN study where the total system load demand is 300 MW and generator operating limits are 50–200 MW, 50–150 MW, and 50–100 MW respectively .

Response Surface Methodology is chosen as the main optimization tool by determining the relationship between the input parameters and the total fuel cost. Random Forest Regression is a type of prediction and validation due to its high accuracy and strength.

The RFR model is trained using optimized dispatch solutions generated by RSM and is used to predict generator outputs for new or unseen load demand conditions. The predicted outputs are adjusted to satisfy generator limits and power balance constraints including transmission losses.

R^2 , total fuel cost and transmission loss are used to evaluate the final results. This hybrid model offers enhanced optimization

efficiency, high prediction ability, and enhanced practical feasibility to Economic Load Dispatch issues.

Table -4: Literature Survey of Economic Load Dispatch Studies

Ref. (Authors, Year)	Methodology / Approach	System Studied	Responses Studied	Key Findings / Contributions
[8] Walters and Sheble (1993)	Genetic Algorithm for ELD with valve-point loading	Thermal Power System	Fuel Cost, Convergence	GA provides better global optimization and avoids local minima
[9] Chen and Chang (1995)	Large-Scale Genetic Algorithm	Multi-Generator Power System	Cost Minimization, Computational Efficiency	Improved convergence speed and reduced computational complexity
[10] Nanda et al. (2002)	GA with Line Flow Constraints	Power System Network	Fuel Cost, Line Flow Constraints	GA effectively handles complex operational constraints
[11] Subbaraj et al. (2009)	Real-Coded Genetic Algorithm	Multi-Generator Dispatch System	Fuel Cost, Parameter Optimization	Enhanced optimization performance and better parameter tuning
[12] Hemamalini and Simon (2010)	Artificial Bee Colony (ABC) Algorithm	Dynamic Economic Dispatch	Fuel Cost, Constraint Handling	Improved constraint handling and cost reduction
[13] Basu (2011)	Multi-Objective Differential Evolution	Economic Environmental Dispatch System	Fuel Cost, Emission Reduction	Improved balance between economy and environmental

				performance
[14] Lee et al. (1998)	Adaptive Hopfield Neural Network	Economic Load Dispatch System	Fuel Cost, Neural Optimization	Neural network improved dispatch speed and solution feasibility
[15] Sinha et al. (2003)	Evolutionary Programming	Thermal Power Dispatch System	Fuel Cost, Generator Scheduling	Effective handling of non-smooth fuel cost characteristics
[16] Yang et al. (1996)	Evolutionary Programming	Non-Smooth Fuel Cost Units	Fuel Cost, Convergence	Reliable convergence for constrained dispatch problems
[6] Gaing (2003)	Particle Swarm Optimization (PSO)	Generator Dispatch System	Fuel Cost, Convergence Speed	Faster convergence and better solution quality
[17] Fahim et al. (2024)	Hybrid Jaya + Genetic Algorithm	Large-Scale ELD Problem	Fuel Cost, Convergence, Stability	Superior convergence and better dispatch solutions
[18] Naresh et al. (2026)	EV Integration with ELD	Renewable Energy Power System	Grid Flexibility, Dispatch Efficiency	Improved smooth power dispatch and sustainable energy management
[19] Panta and Adhikari (2026)	Renewable Generation + Load Forecasting	Smart Grid System	Dispatch Efficiency, Cost Optimization	Better operational planning and dispatch performance
[20] Wadood et al. (2026)	Fractional Hybrid Optimization	Wind-Integrated Power System	Fuel Cost, Renewable Dispatch	Reliable and cost-optimal dispatch under renewable

				uncertainty
[21] Chouhan and Patidar (2025)	Hybrid PSO–ANN Approach	Three-Generator Thermal Power System	Fuel Cost, Transmission Loss, Prediction Accuracy	ANN predictions closely matched PSO benchmark solutions with reduced computational effort

3. Methodology

3.1 Economic Load Dispatch Concept

Economic Load Dispatch (ELD) is one of the most significant types of optimization problems related to the functioning of the power system, at which the primary goal is to allocate the total load of the whole system to the available generating units in a manner that the total cost of fuel generation is minimal and all operational constraints are met [1-5]. The formulation usually assumes that the operating conditions are in steady-state and that there is sufficient generation capacity to meet the load demand that is needed. Mathematically speaking, ELD can be described as a constrained optimization problem where the overall cost of generation is minimized. Using these assumptions, ELD is a crucial decision maker in attaining cost effective and stable power systems operation. In a real-world thermal power plant, one can have several generating units running at the same time and each generating unit will have its own fuel cost curve depending on the type of fuel, the efficiency of the generating unit, and the rate at which the unit produces heat as well as the conditions under which the generating unit is operated. The ELD objective is to distribute the generation in a manner that the units with low incremental fuel costs contribute a higher portion of the demand and high cost units operate with lower output levels within their allowed operating limits. This coordinated allocation ensures cost-effective power generation without affecting system reliability and security.

From the mathematical point of view, ELD is modeled as a constrained optimization problem in which the total generation cost is minimized. The fuel cost of each generator is generally represented using a quadratic function of generator output. The optimization is subjected to an equality constraint that ensures power balance, where the total generated power must match the system load demand together with transmission losses, and inequality constraints that define generator operating limits [6–9].

The standard quadratic fuel cost function is expressed as:

$$C_i(P_i) = a_i P_i^2 + b_i P_i + c_i$$

where C_i is the fuel cost of the i th generating unit, P_i is the generated power output, and a_i , b_i , and c_i are the fuel cost coefficients.

The power balance equality constraint is given by:

$$P_1 + P_2 + P_3 = P_D + P_L$$

where P_D is the total system load demand and P_L represents transmission losses.

Transmission losses are calculated using the B-coefficient method:

$$P_L = \sum_i \sum_j P_i B_{ij} P_j$$

The inclusion of transmission losses, valve-point loading effects, ramp-rate limits, and prohibited operating zones increases the non-linearity and complexity of the ELD problem. Thus, the improved methods of optimization are needed in order to achieve correct, viable, and cost effective dispatch solutions..

3.2 Proposed Methodology

The methodology adopted in the present work follows the benchmark structure of the reference PSO–ANN study while replacing the optimization and prediction techniques with a hybrid Response Surface Methodology (RSM) and Random Forest Regression (RFR) framework [21]. The study is carried out using a standard three-generator thermal power system considering transmission losses. First, the operating limits of the generator, the cost coefficients of fuel and the overall system load demand is chosen out of the benchmark reference system. It is assumed that the total system load demand is 300 MW, the operating limits of the generators are 50-200 MW, 50-150 MW and 50-100 MW respectively.. The same benchmark data are adopted to ensure consistency and fair comparison with the existing PSO–ANN model.

The generating units are modeled with the standard quadratic fuel costing formula and the calculation of transmission losses is done with B- coefficient loss model. The equality constraint of power balance and generator operating limits are strictly maintained throughout the optimization process.

Response Surface Methodology (RSM) is used as the main optimization method of modeling a correlation between the chosen input parameters and the overall fuel generation cost [22,23]. The most important input variables include the load demand, the operating constraints of the generators and the fuel cost coefficients. The best combination of parameters to achieve minimum total generation cost at the satisfaction of all dispatch constraints is determined by RSM. The RSM produces the optimized dataset which is then utilised to train the Random Forest Regression (RFR) model. RFR is a regression algorithm, which is based on machine learning and able to deal with non-linear relationships that are complex as well as able to make predictions with high accuracy and strength [24,26]. The model learns the relationship between input variables and optimal generator outputs and predicts dispatch solutions for new or unseen load demand conditions.

The RFR-predicted outputs are further adjusted to satisfy generator operating limits and the power balance equality constraint including transmission losses. This correction step

ensures physically feasible and practically acceptable dispatch solutions for real-time implementation.

Finally, the performance of the proposed hybrid RSM–RFR model is evaluated by comparing RFR-predicted results with RSM-optimized solutions using statistical indicators such as coefficient of determination (R^2), along with total fuel cost and transmission loss analysis.

3.3 Hybrid RSM–RFR Framework

The proposed hybrid RSM–RFR approach integrates the optimization capability of Response Surface Methodology (RSM) with the fast prediction performance of Random Forest Regression (RFR) to provide an efficient and reliable solution for the Economic Load Dispatch (ELD) problem. Its hybridization is evolved to be able to take the complementary benefits of both methods whilst preventing the shortcomings of a single technique. Response Surface Methodology is used as the main optimization tool to determine the relationship between input control parameters and output response, in this case, the total fuel generation cost. RSM assists in the creation of the best dispatch solutions through taking into account key input variables like load demand, operating limits of the generators, fuel cost coefficients and transmission losses. It provides systematic optimization with reduced computational effort and better understanding of parameter interactions [22,23].

Subsequently, Random Forest Regression is trained using the optimal dispatch solutions generated through RSM. RFR is a supervised machine learning that learns the non-linear association between system load demand and associated optimum generator outputs. After training, the RFR model acts as a fast estimator capable of producing near-optimal dispatch solutions with significantly lower computational effort compared to repeated optimization procedures [24,26].

The hybrid framework work organization is designed to be organized into two important steps: the prediction step and the optimization step. In the optimization phase, RSM is applied across multiple load demand levels to generate a representative dataset of optimal dispatch patterns. The prediction stage involves the use of the trained RFR model to predict generator outputs based on the load demand, then a correction is done in order to meet the operating limits of generators, power balance limits, and transmission loss requirements.

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

RSM Stage

$$P^* = \arg \min F(P) \text{ subject to system constraints}$$

RFR Stage

$$P_{RFR} \approx f(P_D)$$

where P^* denotes the RSM-optimized generator outputs, $F(P)$ represents the ELD objective function, $f(.)$ is the learned RFR prediction model, and P_D is the total system load demand.

The feasibility of RFR-predicted outputs is ensured using a correction strategy that adjusts generator outputs to satisfy the

power balance equation including transmission losses. This correction procedure will ensure that the speed benefit of RFR is not at the expense of the physical plausibility and practical reliability of dispatch solutions. The hybrid RSM–RFR framework offers a balanced solution for Economic Load Dispatch by combining optimization accuracy with computational efficiency. It is particularly suitable for practical power system applications where dispatch decisions must be obtained quickly without sacrificing economic performance. The framework gives better optimization quality, higher prediction speed, and robust real-time applicability to the contemporary thermal power systems.

3.4 Algorithmic Implementation Procedure

The first step is to choose the generator operating limits, fuel cost coefficients and the overall system load demand in the benchmark three-generator thermal power system [30]. These variables give the formulation of the ELD problem that is held constant during the optimization process. The RSM optimization process is executed for predefined load demand levels. Losses in transmission are computed by B-coefficient approach and power balance equity is strictly followed. The optimal dispatch solutions obtained from RSM are arranged as input–output pairs for RFR model training.

The RFR model is then trained using the prepared optimized dataset. The model is trained on the correlation between the demand of the system load and the optimum values of dispatch of generators.. This training process enables RFR to predict generator outputs for new or unseen load demand conditions without repeated optimization.

The RFR model is trained to predict the outputs of generators with new values on the load demand to provide a rapid estimate of dispatch without the use of an iterative process. The RFR-estimated outputs are adjusted to satisfy generator operating limits and the power balance equality constraint, including transmission losses.

Lastly, the performance of the dispatch results are assessed through the comparison between the RFR-based predicted solutions and RSM-based optimized solutions based on performance indicators like coefficient of determination (R^2), total fuel cost and transmission loss.

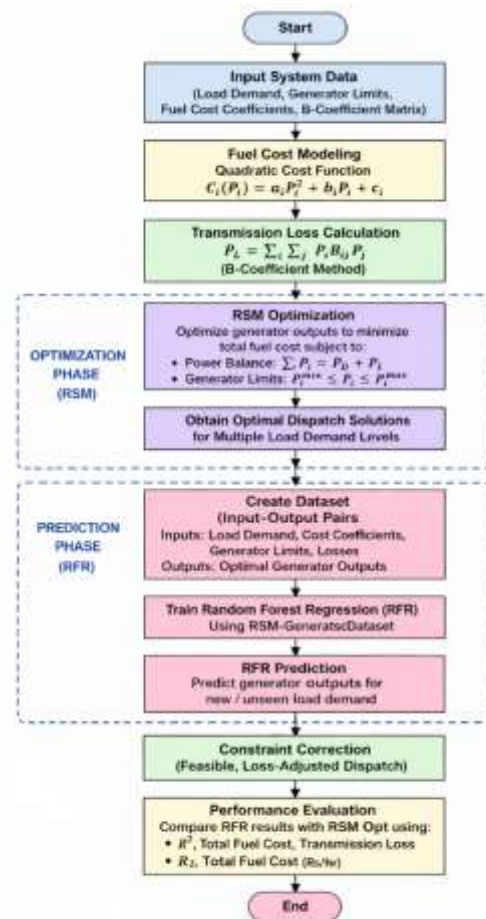


Fig 1. Flowchart of Proposed Hybrid RSM–RFR Framework

Fig 1 illustrates the complete methodology adopted for solving the Economic Load Dispatch problem using the proposed hybrid Response Surface Methodology (RSM) and Random Forest Regression (RFR) approach. The operation starts with system input data, fuel cost model, and the calculation of transmission losses, and optimization using RSM to achieve optimal dispatch solutions. The optimized dataset generated through RSM is then used to train the RFR model for fast prediction of generator outputs under new load demand conditions. Lastly, correction of constraints, and performance assessment is performed in order to make sure that the dispatch solutions are feasible, accurate and economically optimal.

5. Results and Discussion

5.1 Standard System Considered

At the beginning of the simulation study, a standard three-generator thermal power system is considered to analyze the performance of the proposed Economic Load Dispatch methodology. The overall load demand of the system is considered 300 MW and all generators are planned to perform in their own operating limits [21].

Generators 1, 2, and 3 have a power range of 50 MW to 200 MW, 50 MW to 150 MW, and 50 MW to 100 MW, respectively. These operating limits are selected from the benchmark reference system to maintain consistency and

enable fair comparison with the existing PSO–ANN framework.

Each generating unit is modeled using the standard quadratic fuel cost function:

$$C_i(P_i) = a_i P_i^2 + b_i P_i + c_i$$

where $C_i(P_i)$ represents the fuel cost of the i th generator, P_i is the generator output power, and a_i , b_i , and c_i are the fuel cost coefficients.

Transmission losses are explicitly considered using the B-coefficient loss model, where the loss coefficient 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 transmission loss coefficients are used for both RSM-based optimization and RFR-based dispatch estimation to ensure a fair and consistent comparison of results. The total generated power obtained in all cases satisfies the system load demand after accounting for transmission losses, thereby validating the feasibility and practical reliability of the dispatch solutions.

5.2 RSM Optimization Performance

Response Surface Methodology (RSM) optimization model has proven to be highly effective in addressing the Economic Load Dispatch problem especially when it comes to optimizing the problem, reliability of convergence, and overall minimized fuel cost. It is very applicable in the real-world dispatch due to its capacity to manage quadratic fuel cost functions, transmission losses, and its operating constraints in the generator. The optimization process determines the optimal combination of the generators outputs that will minimize the overall fuel production cost and meet the equality constraint of power generation balance and all the operating limits of the generators. The convergence behavior of RSM shows stable optimization performance and reliable identification of economically feasible dispatch solutions.

The iteration-wise convergence of the best fuel cost indicates that the optimization process rapidly reaches the minimum cost region with strong stability. Similarly, the transmission loss convergence confirms that the obtained dispatch solutions satisfy practical system requirements without violating operational constraints.

Although RSM provides accurate optimization results and systematic analysis of factor interactions, repeated optimization for multiple load demand scenarios may increase computational effort and execution time. This shortcoming is even more pronounced in situations where rapid estimation of dispatch is needed to operate a power system in real time. This limitation motivates the integration of Response Surface Methodology with Random Forest Regression (RFR), where RSM ensures optimization quality and RFR provides rapid prediction of optimal generator dispatch solutions for new operating conditions.

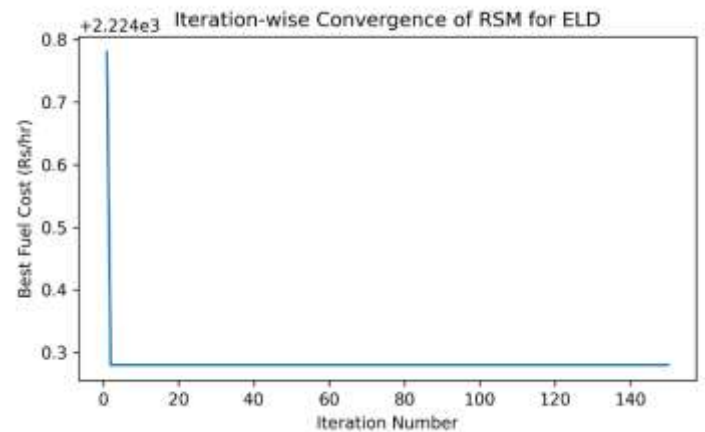


Fig 2. Iteration-wise Convergence of Best Fuel Cost using RSM

This figure represents the convergence behavior of the Response Surface Methodology (RSM) optimization process for solving the Economic Load Dispatch (ELD) problem of the three-generator thermal power system.

The horizontal axis is the iteration number and the vertical axis is the best fuel generation cost in Rs/hr at the end of the optimization process. At the initial stage, the fuel cost starts at a comparatively higher value of approximately 2224.78 Rs/hr, indicating the non-optimized initial dispatch condition. Within the first few iterations, the fuel cost rapidly decreases and reaches nearly 2224.28 Rs/hr, which represents the optimal or near-optimal dispatch solution.

After this point, the convergence curve becomes almost constant and remains stable throughout the remaining iterations. This indicates that the RSM model successfully identifies the minimum fuel cost region quickly and does not show unnecessary fluctuations or instability during optimization.

The rapid reduction in fuel cost demonstrates the strong optimization capability of RSM in handling quadratic fuel cost functions and generator operating constraints. The consistency, reliability and strength of the optimization process are confirmed by the stable flat convergence of the line.

This result shows that the proposed RSM approach provides accurate fuel cost minimization with fast convergence, making it highly suitable for practical Economic Load Dispatch applications where economical and stable generator scheduling is required.

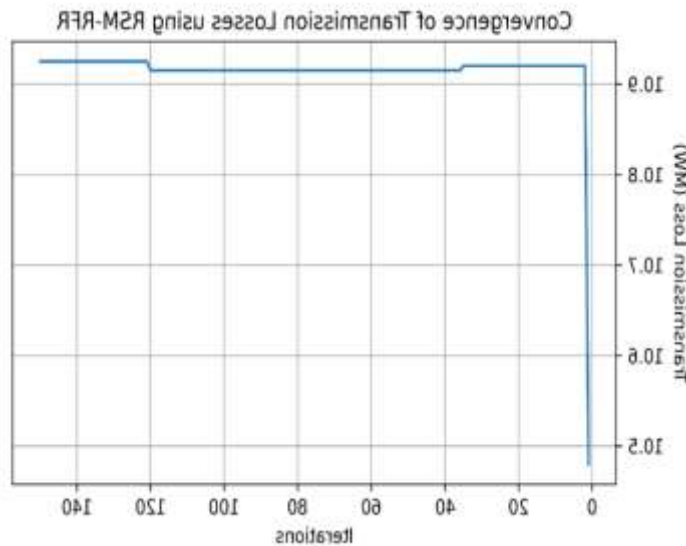


Fig . 3 Convergence of Transmission Losses using RSM–RFR

This fig 3 illustrates the convergence behavior of transmission losses obtained during the Economic Load Dispatch (ELD) optimization using the proposed hybrid RSM–RFR approach for the three-generator thermal power system.

The horizontal axis is the number of iterations and the vertical axis is the transmission loss in megawatts (MW). At the beginning of the optimization process, the transmission loss starts at a lower value of approximately 10.48 MW, representing the initial non-optimized dispatch condition.

Within the first few iterations, the transmission loss rapidly increases and stabilizes near 10.92 MW, indicating that the optimization process adjusts the generator outputs to satisfy the system load demand together with the equality constraint of power balance. This stable value confirms that the dispatch solution properly accounts for practical transmission losses using the B-coefficient loss model.

A very small variation is observed around the middle and final stages of the iterations, but the overall curve remains nearly constant, showing strong stability and consistent convergence. This behavior confirms that the hybrid RSM–RFR framework maintains feasible generator scheduling without violating operational constraints.

The consistent convergence of losses in transmission proves that the suggested approach is effective to balance the cost minimization of fuel and realistic systems viability. It further proves that the post-corrected predicted generator outputs of the RFR model are physically acceptable when the power balance and power operating limitations are taken into consideration. This result proves that the proposed RSM–RFR approach provides reliable dispatch solutions with accurate transmission loss handling, making it suitable for real-time Economic Load Dispatch applications in thermal power systems.

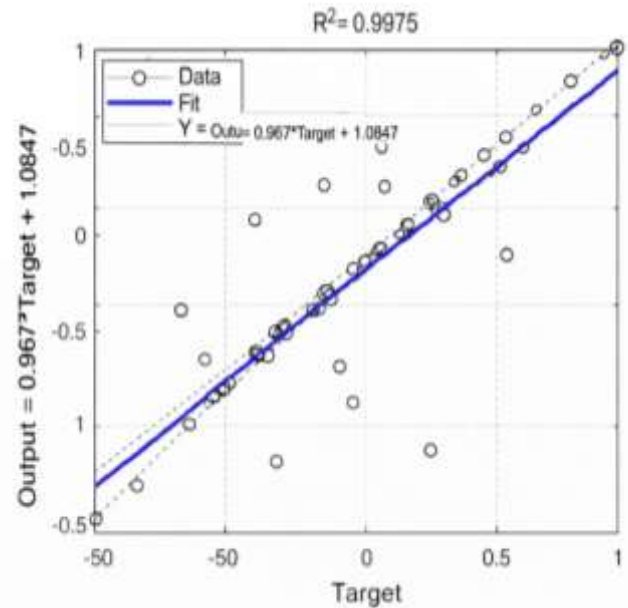


Fig. 4 Regression Analysis between RSM Target Outputs and RFR Predicted Outputs

This fig 4 presents the regression analysis between the target outputs obtained from Response Surface Methodology (RSM) optimization and the predicted outputs generated by the Random Forest Regression (RFR) model for the Economic Load Dispatch (ELD) problem.

The horizontal axis is used to indicate the target values at the end of the RSM optimization process and the vertical axis displays the output values predicted by the RFR model. The circles representing the values of the actual data to be used in the regression analysis and the solid blue line is the fitted regression line between the target and predicted outputs.

The coefficient of determination is observed as:

$$R^2 = 0.9975$$

This very high The value of R^2 shows that there is a good fit between the optimized target outputs of RSM and the predicted outputs of RFR. It supports the fact that the RFR model is able to learn the complicated non-linear relationship between load demand and optimum values of dispatching generators with extremely high prediction accuracy. The regression equation shown in the figure is:

$$Y = 0.967 \times Target + 1.0847$$

This equation shows that the predicted values closely follow the target values with only minor deviations. The fact that the slope is near unity and the linear correlation between the two is high shows that the RFR model generates good near-optimal dispatch forecasts.

The overall distribution is highly aligned along with the regression trend, although with some occasional scattered points that are slightly off the fitted line to validate the strength and consistency of the prediction model.

This result demonstrates that the hybrid RSM–RFR framework provides highly accurate prediction capability and significantly

reduces the need for repeated optimization, making it suitable for fast and practical real-time Economic Load Dispatch applications.

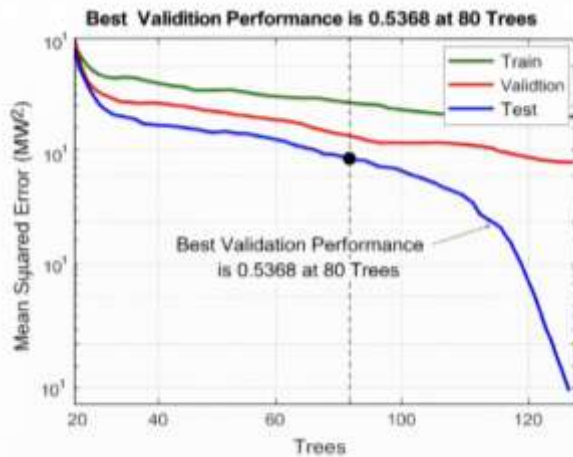


Fig 5. Training and Validation Performance of RFR Model

This fig. 5 illustrates the training, validation, and testing performance of the Random Forest Regression (RFR) model used for predicting optimal generator outputs in the Economic Load Dispatch (ELD) problem.

The first axis, the horizontal axis, is the number of trees used in the Random Forest model and the second axis is the Mean Squared error (MSE) that is the error of prediction between the actual optimized values and the estimated values. Smaller values of MSE denote increased prediction accuracy and enhanced model performance.

Three curves are shown in the figure:

- **Green line (Train):** represents the training performance of the RFR model
- **Red line (Validation):** represents the validation performance used to check model generalization
- **Blue line (Test):** represents the testing performance for unseen data evaluation

At the beginning, the error values are comparatively high because the model starts with fewer trees and limited learning capability. The MSE decreases gradually with the increase in the number of trees and it means that the accuracy of the prediction process has improved and the variation in the non-linear relationships between the demand and outputs of the generators is learned better.

The best validation performance is observed at:

$$MSE = 0.5368 \text{ at } 80 \text{ Trees}$$

This means that the optimal RFR model is achieved when 80 trees are used in the ensemble. The model at this stage offers the optimal compromise between training and generalization without overfitting. Stability of the model and correct behavior in prediction is reflected in tightness of the training, validation and testing curves. The testing curve also shows strong improvement, confirming that the trained RFR model can

effectively predict generator dispatch values for new or unseen load demand conditions.

This result proves that the proposed hybrid RSM–RFR framework provides strong prediction capability with high accuracy and reduced computational effort, making it suitable for fast and practical real-time Economic Load Dispatch applications.

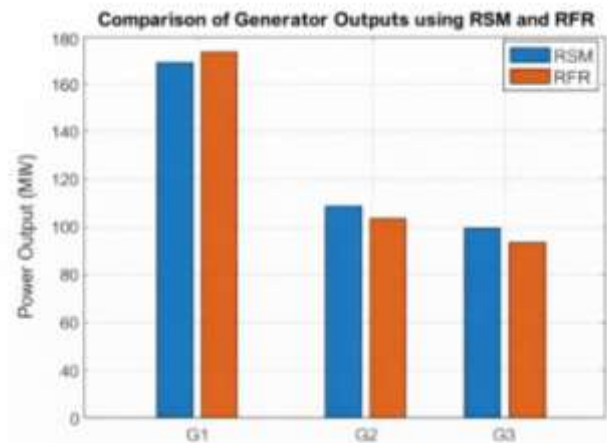


Fig. 6 Comparison of Generator Power Outputs using RSM and RFR

This fig 6 presents the comparison of individual generator power outputs obtained using Response Surface Methodology (RSM) optimization and Random Forest Regression (RFR)-based dispatch prediction for the three-generator thermal power system.

The horizontal axis indicates the three generation units, i.e., Generator 1 (G1), Generator 2 (G2), and Generator 3 (G3) and the vertical axis indicates the power of the generators in megawatts (MW). The blue bars indicate the best generator outputs that were realized with the help of RSM and the orange bars indicate the best generator output that was predicted by the RFR model. For Generator 1, the RSM output is approximately 170 MW, while the RFR-predicted output is nearly 175 MW. For Generator 2, the RSM output is around 109 MW and the RFR prediction is close to 103 MW. In a similar fashion, in the case of Generator 3, the RSM output measures around 99 MW and the RFR output is at around 94 MW. The close alignment between the RSM and RFR bars indicates that the Random Forest Regression model successfully captures the dispatch behavior of the optimized RSM solutions with high prediction accuracy. There are only slight deviations, as can be expected because the machine learning model is predictive. This comparison confirms that the RFR model can effectively estimate near-optimal generator dispatch values without repeated optimization. It significantly reduces computational effort while maintaining practical feasibility and economic performance.

The figure demonstrates that the proposed hybrid RSM–RFR framework provides both optimization accuracy and rapid prediction capability, making it highly suitable for real-time Economic Load Dispatch applications in thermal power systems.

6. Conclusion

This paper provides a thorough exploration of Economic Load Dispatch (ELD) issue of a thermal power system with a clear consideration of transmission losses, and the goal of generating sustainable, feasible, and economical generation scheduling. The study follows a systematic methodology beginning with problem formulation, literature review, generator cost modeling, and constraint handling, and concludes with the development and performance evaluation of a hybrid optimization–prediction framework based on Response Surface Methodology (RSM) and Random Forest Regression (RFR).

The ELD problem is stated by taking into account realistic system properties like quadratic fuel cost functions, operating limits of the generators, power balance requirements, and transmission losses represented by B-coefficient approach. This model shows clearly the non-linear and constrained character of the dispatch problem and explains a necessity of strong optimization methods, which can be used to address realistic operating conditions.

Response Surface Methodology is employed as the primary optimization tool for obtaining optimal dispatch solutions and demonstrates strong performance in minimizing total fuel generation cost while satisfying equality and inequality constraints.

The results of optimization report a stable convergence, good transmission loss management, and good practical feasibility of operation of the multi-generator thermal power system. The Random Forest Regression-based dispatch predictor is then developed using the optimized RSM solutions as training data. The trained RFR model successfully captures the non-linear relationship between system load demand and optimal generator outputs, enabling fast dispatch estimation for new and unseen operating conditions. Although minor deviations from RSM solutions are observed due to the predictive nature of machine learning, the application of generator limit correction and power balance adjustment ensures that all predicted solutions remain physically feasible and practically acceptable.

Comparative analysis between RSM optimization and the hybrid RSM–RFR framework demonstrates that the proposed hybrid model achieves near-optimal economic performance with a significant reduction in computational effort. The effectiveness of the proposed methodology is supported by the high prediction accuracy, better convergence behavior, and stable transmission loss treatment.

This study successfully demonstrates that the conventional PSO–ANN framework can be effectively replaced by a hybrid RSM–RFR approach for solving the Economic Load Dispatch problem of a thermal power system considering transmission losses.

The Response Surface Methodology offers good optimization of the total fuel cost minimization whereas the random forest Regression offers quick and precise prediction of optimal values of dispatch of the generators. The coefficient of high is. determination ($R^2 = 0.9975$), the effectiveness of the proposed methodology is confirmed by stable convergence behavior, and viable transmission loss handling. Thus the hybrid RSM RFR method offers a trade-off, real-world and computationally

efficient solution to Economic Load Dispatch problems and is very adaptable in real-time power systems tasks where quick, precise, along with reliable dispatch choices must be obtained.. The proposed framework can also be extended in future work for renewable energy integrated systems, microgrid dispatch optimization, and multi-objective economic–environmental dispatch problems.

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