A Comparative Study on Combined Economic Emission Dispatch using Machine Learning Techniques

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***Abstract*—Economic Emission Load Dispatch (EELD), the combination of economic efficiency and environmental sustainability in power system operation, has arisen as a critical challenge in the current era of power generation and distribution. This review paper provides an in-depth review of the application of machine learning methods to tackle the inherent complexity of EELD. It encompasses the latest advancements and notable trends in this sector. The review begins by explaining the essential concepts and goals of EELD, highlighting the importance of balancing operating costs and lowering greenhouse gas emissions. EELD solutions have been built on traditional optimization approaches such as Linear Programming and Genetic Algorithms. However, machine learning techniques have recently gained popularity due to their capacity to deal with power systems' complex, non-linear interactions. This paper aims to analyze the strengths and limits of several algorithms in optimizing generation schedules while ensuring that they adhere to emission regulations. Moreover, this paper explores the role of data-driven methodologies in EELD, highlighting the importance of precise data collection and preprocessing. This statement elucidates the incorporation of exogenous variables, such as meteorological predictions and energy consumption trends, into EELD (Energy Efficient Load Dispatch) models, emphasizing their influence on augmenting the efficacy of decision-making procedures.**

***Keywords:*Economic Emission load dispatch, Optimization Algorithms, Machine learning Algorithm**

I.Introduction

Electrical power generation predominantly relies on thermal plants fueled by fossil fuels for electricity generation. Efforts should be made to regulate and reduce the utilization of fossil fuels within electrical power-producing systems. The availability of fossil fuel resources in the natural environment is severely constrained and often poses challenges in terms of accessibility[1]. These reserves are concentrated within a limited number of nations, which may exert influence or impose restrictions on the supply of fossil fuels. Researchers are driven to investigate methods of reducing the reliance on fossil fuels in thermal power plants during electricity generation due to the significant pollution to the environment caused by the release of substantial quantities of polluting gas particulates. Despite the development and implementation of different choices, such as power generated using hydroelectric and nuclear sources, fossil fuels remain the predominant source of electricity generation. Therefore, the primary challenges associated with using fossil fuels in power production systems involve identifying an appropriate approach to reduce fuel consumption simultaneously, associated costs, and the emission of harmful pollutants[2]. The Combined Economic Emission Dispatch (CEED) refers to a crucial challenge in the operation of power systems. Its primary objective is determining the most influential generation schedule for power generators. This schedule is designed to minimize the operating cost that comes with power generation while also seeking to reduce the emission of greenhouse gases. In recent years, there has been a growing utilization of machine learning algorithms to tackle obstacles in the field of CEED[3].

The two aims are inherently contradictory and cannot be effectively optimized. The presence of conflicting objectives in this context leads to a problematic multi-objective optimization issue referred to as the combined economic emission dispatch (CEED) problem. In this Problem, both objectives are taken into account and optimized simultaneously.[3] Researchers have proposed many algorithms to solve these EELD problems. Many optimization algorithms like Linear Programming (LP), Quadratic Programming(QP)[4], Non Linear Programming (NLP), Genetic Algorithm (GA)[5], Particle Swarm Optimisation Algorithm(PSO)[6], Improved Swarm Approach[7],Ant Colony Algorithm(ACO), Simulated Annealing(SA)[8], Tabu Search(TS) [9]are utilized in solving this NL problem. Hybrid approaches and dynamic programming methods are adopted to get the most accurate scheduling to solve the EELD problem.

In recent days, [9]Machine learning algorithms like Artificial neural network(ANN)[9], Support Vector Machines(SVM)[10], Random Forest(RF), Gradient Boosting Algorithm(GBA), Reinforcement Learning (ReL), K means Clustering, K Nearest Neighbour(KNN), and many other Deep Neural Networks (DNN) [11]are utilized in solving this EELD problem.

Thermal power facilities, which utilize fossil fuels, continue to serve as the primary source of electrical power generation. The finite nature of fossil fuel reserves, the geopolitical control over these resources, and the environmental harm caused by emissions all present significant challenges that this reliance must address. Although alternative energy sources such as hydroelectric and nuclear power have made progress, fossil fuels continue to be essential for electricity generation because of their established infrastructure and ability to meet large-scale demand.

The Combined Economic Emission Dispatch (CEED) problem encompasses the intricate objective of determining the optimal generation schedule that minimizes both emissions and operating costs. This objective is a multi-objective optimization problem due to its dual character, which seeks to reduce environmental impact and reduce costs. Over the years, researchers have endeavored to achieve a compromise between these opposing objectives by developing and refining a variety of optimization techniques.

Traditional Methods and Early Approaches:

Classic mathematical optimization techniques were initially employed to address the EELD problem:

Cost-efficient power generation schedules were frequently computed using Linear Programming (LP)[12], Quadratic Programming (QP)[13], and Dynamic Programming (DP)[14]. Nevertheless, these methods were unable to adequately account for the non-linear character of power systems and emissions.

While Non-Linear Programming (NLP) provided superior capabilities for managing non-linearities, it necessitated substantial computational capacity, which restricted its application to smaller systems.

Although these methods established a strong foundation, they were unable to address the progressively intricate demands of contemporary power systems that incorporate renewable energy sources and experience dynamic demand shifts.

Transition to Heuristic and Metaheuristic Algorithms

As the complexity of power systems increased, researchers pursued more effective optimization tools:

GA: These algorithms, which were motivated by the process of natural selection, gained popularity due to their capacity to rapidly identify solutions that were nearly optimal. In an effort to optimize power generation schedules with minimal cost and emissions, GAs emulate the biological process of evolution by selecting, crossing, and mutating solutions.

PSO: The collective behavior of birds and fish served as an inspiration for PSO, which provided a more direct and expeditious alternative to GAs. It allowed researchers to more effectively optimize non-linear and multi-objective functions by simulating a group of particles (solutions) that traverse the solution space.

Simulated Annealing (SA), Tabu Search (TS), and Ant Colony Optimization (ACO): These algorithms expanded the toolkit of heuristic approaches by introducing a variety of mechanisms for investigating the solution space and avoiding local optima. For instance, ACO employed the concept of pheromone traces to replicate the behavior of ants in identifying paths, which was appropriate for resolving routing issues in power systems.

The emergence of multi-objective optimization

It was evident that the analysis of economic costs and emissions in isolation was ineffective. This realization resulted in the development of multi-objective optimization techniques:

Pareto-Optimal Solutions: These methods enabled operators to evaluate a variety of alternatives that illustrated the trade-offs between reducing emissions and minimizing costs. The Pareto front solutions represented scenarios in which no single objective could be enhanced without weakening another.

Fuzzy Logic Integration: This method facilitated decision-making in uncertain environments by enabling more flexible, human-like reasoning. In order to modify the objectives in response to real-time data and evolving conditions, researchers integrated fuzzy logic with PSO and other algorithms.

The Revolution in EELD Driven by Machine Learning (ML): Machine learning has enabled the management of the intricate, data-rich nature of EELD, with a significant breakthrough:

Artificial Neural Networks (ANNs): As early ML models were applied to EELD, ANNs were regarded for their capacity to understand patterns from historical data. They were notably effective in predicting optimal generation schedules by analyzing historical scenarios and environmental conditions.

Support Vector Machines (SVMs) were employed due to their capacity to classify various load dispatch strategies and manage high-dimensional data, thereby ensuring that solutions were more precisely tailored to the constraints of EELD issues.

Random Forests (RF) and Gradient Boosting Algorithms (GBA) are ensemble methods that enhance prediction accuracy by combining multiple decision trees. Their resilience rendered them appropriate for managing fluctuations in power demand and generation.

Developments in Deep Learning

The advent of deep learning resulted in the development of more advanced models:

Recurrent Neural Networks (RNNs): These models were notably influential in EELD due to their ability to accommodate temporal dependencies and sequential data. Researchers were able to more effectively manage fluctuations in renewable energy supply and anticipate shifts in power demand as a result of the use of RNNs.

Deep Neural Networks (DNNs): By capturing intricate, non-linear relationships within extensive data sets, DNNs have made substantial contributions. Their depth and multiple layers provided a higher level of representation capacity, rendering them valuable for adaptive scheduling and long-term load forecasting.

Hybrid Methodologies: Integrating Machine Learning and Conventional Approaches

Researchers acknowledged that hybrid models, which integrated traditional optimization algorithms with machine learning, produced superior outcomes:

The integration of ANNs with PSO is a method that employs the predictive potential of neural networks to estimate initial solutions, which can then be refined by PSO. This method combined the learning capabilities of ANNs with the quickness and adaptability of PSO, resulting in a more precise and efficient scheduling process.

Heuristic Methods Assisted by Machine Learning: In real-time applications, machine learning models have enabled the refinement of heuristic algorithms by learning from past outcomes, thereby reducing the necessity for trial-and-error analysis.

Adaptive and Real-Time EELD Models

Advancements in sensor technology, data availability, and processing capacity have facilitated the development of real-time models:

Adaptive Dispatch Systems: These systems have the potential to optimize cost and emissions by adjusting generation schedules in real-time, using data such as weather forecasts. This was especially important for circuits that contained renewable energy sources, which are inherently variable.

Reinforcement Learning (RL): RL models dynamically adapt to shifting conditions by learning from continuous feedback. This method facilitated the development of decision-making that was more effective over time, as it was able to balance emissions and costs as external conditions changed.

This article aims to give a clear explanation of EELD, its constraints, advantages , Challenges faced, Methodologies Adopted, Optimization Techniques (OT) used in solving EELD, Machine Learning Techniques (ML) for EELD Problems, and comparison of OT and ML in solving EELD and concluded with Future scope.

II. EELD Problem

The term EELD [15] typically pertains to optimizing fuel cost and reducing hazardous gas emissions and particulate matter while simultaneously meeting the overall load demand and adhering to certain equality and inequality limitations[16]. However, in addition to the aims above, several researchers consider additional factors such as stability level, load modification time, reserve capacity, and transmission loss while addressing the EELD problem. The EELD is commonly depicted as a quadratic cost function by researchers and is characterized as such in eq,1

$$F(P_{gi}) = \sum_{i=1}^{n} \mathbf{aiPgi2 + biPgi + c_i} \qquad (1)$$

The variable F represents the overall fuel cost per hour divided by the generation cost in dollars. The coefficients a_i, b_i, and c_i correspond to the fuel cost of the i-th generating unit[16]. Furthermore, the P_{gi} represents the actual power generation of the ith unit, measured in megawatts (MW), whereas the variable n denotes the total number of generating units. The emission dispatch problem is sometimes expressed as a quadratic function, which can be defined as follows.

$$E(P_{gi}) = \sum_{i=1}^{n} \mathbf{diPgi2 + eiPgi + fi} \qquad (2)$$

The emission function, denoted as E and measured in kilograms per hour (kg/h), and the emission coefficients of the ith generating unit, represented as d_i, e_i, and f_i. The two aims are inherently incompatible and contradictory, leading researchers to occasionally merge them into a singular objective using a price penalty component. The economic emission function F_T, which is measured in (\$/h) and has a penalty factor, can be defined as follows:

$$FT=\sum_{i=1}^{n}\{F(Pgi) + hiE(Pgi)\} \quad (3)$$

The penalty factor, denoted as h_i, is expressed in units of dollars per kilogram (\$/kg).

Researchers must consider the many real-time and practical restrictions present in power generation systems to produce accurate and dependable power generation results that can be used in power generation systems.

III. Elements of EELD

a.Power Balance Constraint(PBC): The PBC necessitates that the aggregate power provided by all generating units must be sufficient to meet the overall load demand.

$$P=\sum_{i=1}^{n} \mathbf{Pgi = PD + PL}(4)$$

The variables P, P_{gi}, P_D, and P_L represent the total generated power in all generating units, the total generated power in generating unit I, the total power demand, and the total loss, respectively.

b. Constraint due to Transmission loss(TLC): TLC refers to the reduction in electrical power that occurs when power generated in a power generation system is transmitted to the grid. The phenomenon referred to as transmission loss is a significant limitation in EELD difficulties.

$$PL = \sum_{i=1}^{n} \sum_{j=1}^{n} PgiBijPgj + \sum_{i=1}^{n} BioPgi + B00(5)$$

The variables Bij, Bi0, and B00 represent the loss coefficients in George's formula, the transmission loss constant of generating unit i, and Kron's transmission loss constant, respectively.

c. Generator limit Constraint(GLC):

[16] Each unit's generated total powermust remain between its upper and lower limits for reliable power system operation. It can be characterized as follows:

$$\mathbf{Pgi, Min \leq Pgi \leq Pgi, max}(6)$$

The variables Pgi,min, and Pgi,max represent the lower and upper bounds of the power output of generating unit i.

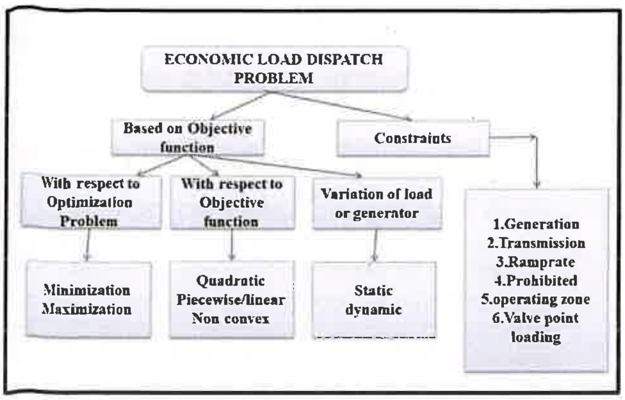

Figure 1:Elements of Economic Load Dispatch

d. Ramp Rate Constraint(RRC): The generator ramp rate restriction imposes realistic constraints on the operational range of all generating units. Consequently, they must function within two contiguous and distinct operational areas. To appropriately develop the EELD, [16]it is imperative to consider the limitations imposed by the generator ramp rate. Considering the ramp rate restriction, each generating unit's power output can be expressed as follows.

$$\mathrm{Max}(Pgi,\min, Pgi0 - DRi) \leq Pgi \leq \mathrm{Min}(Pgi,\max, Pgi0 + URi)$$
(7)

The variable Pg_{i0} represents the previous operating point of generating unit i. Also, DRi and URi denote the down and up rate limits of generating unit i, respectively.

e. Prohibited operating zones(POZ): POZ are common in real power production systems, where the complete operating range of a generating unit may not always be accessible for operation. Specific units may experience restricted operating zones due to physical operational limitations, and operating inside these zones can potentially result in instabilities[17]. Therefore, it is imperative that the generation output refrains from operating within the designated forbidden operating zones. The generating unit should run within the feasible operating zones as described below.

$Pgi,\min \leq Pgi \leq Pgil,1$ (8)

$PgiU,j - 1 \leq Pgi \leq PgiL$, jj=2,3,…$K_i$ (9)

$PgiU,Ki \leq Pgi \leq Pgi,\max$ (10)

The symbol K_i denotes the quantity of restricted operating regions within the curve of generating unit i, with j being the index of a specific restricted operating region for generating unit i. The lower limit of the jth prohibited zone denoted as P_{gij}^{L}, and the upper limit of the (j-1)th prohibited operating zone, denoted as Pgi j U, are the respective limits for the generating unit i.

IV. Pros of Accurate EELD

a. Economic Efficiency:The primary objective of the EELD initiative is to reduce the operational expenses associated with power generation. [18]Power utilities can minimize fuel use and operational expenses by optimizing resource allocation, significantly reducing costs.

b. Environmental Sustainability: The EELD framework considers the concurrent mitigation of greenhouse gas emissions. It facilitates the attainment of environmental objectives [19]and mitigating the carbon emissions associated with electricity production, following international endeavors to address climate change.

c. Optimal Resource Allocation: The EELD framework aims to maximize the utilization of diverse generation sources, encompassing conventional fossil fuels, sustainable renewable energy, and advanced energy storage technologies. This practice guarantees the efficient utilization of resources, facilitating the integration of cleaner energy sources into the power system.

d. Flexibility: The EELD system can effectively respond to fluctuations in electricity demand, variations in fuel costs, and the accessibility of renewable energy sources. [15]Flexibility allows for adjusting the generation mix to respond to changing conditions effectively.

e. Compliance with laws: Numerous regions and countries have implemented rules and standards to reduce emissions. The EELD program assists electricity utilities in achieving regulatory compliance while simultaneously ensuring cost-effective operational practices.

f. Enhanced decision support: Economic and environmental decision-making can benefit significantly from EELD models since they offer vital insights into the inherent trade-offs between these objectives[20]. The data provided by the EELD facilitates the process of making well-informed decisions on power generation and policy.

g. Integration of renewable energy: Incorporating renewable energy sources, such as wind and solar, into the generation mix can be efficiently achieved using EELD[21]. The seamless integration of renewable energy into the existing power grid is facilitated by strategically optimizing clean energy use in conjunction with traditional energy sources.

h. Reduced Fuel Consumption: The utilization of EELD models has the potential to reduce the consumption of fossil fuels by optimizing the dispatch of generators at their optimal operating points. This leads to a decrease in gasoline usage and reduced associated expenses.

The emphasis of CEED on the cost-effective production of energy can reduce power costs for consumers, providing advantages to both industrial and residential users.

V. Methodologies Adopted

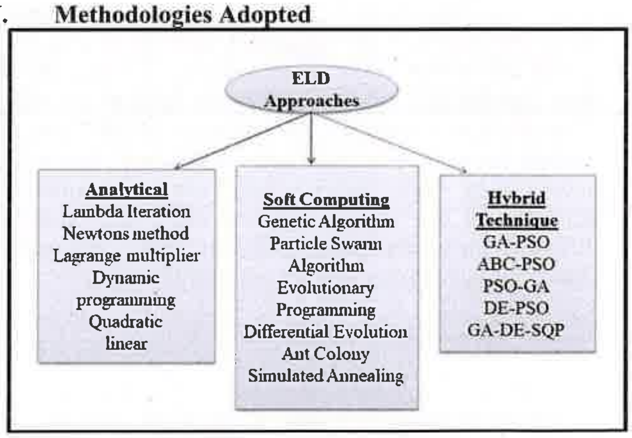

Figure 2: ELD Approaches

Numerous studies demonstrate that numerous optimization algorithms have been used to resolve high-complexity economic load dispatch problems. Basic analytical approaches, such as Lambda iteration, Newton's method, and The Lagrange multiplier approach, can address the ELD problem with an assumption that the incremental cost curves of the generating units exhibit a monotonically growing piecewise-linear pattern. Acknowledging that the fuel cost function has non-convex characteristics in practice is essential. Traditional methods based on classical calculus are inadequate in effectively addressing this Problem. The dynamic programming method can be employed to address the issue at hand. It is challenging to handle the ELD problem due to the presence of cost curves that are intrinsically non-linear and discontinuous. However, the computational aspect of solving this Problem remains a significant obstacle. The algorithm exhibits high complexity and is prone to encountering local optima due to premature convergence.

However, to address the limitations associated with the non-linear cost curves, one-way search, early and late convergence, and sub-optimal solutions, many stochastic and smart approaches were employed to effectively solve the ELD Problem.[21]The [22] researchers encompassed techniques to solve Multi-objective problems consisting of GA, PSO, Evolutionary Programming (EP), Differential Evolution (DE), ACO, Simulated Annealing (SA), Gravitational Search Algorithm (GSA), Biogeography-Based Optimization (BBO), Sequential Quadratic Programming (SQP), etc. In contrast to classical optimization methods, intelligent stochastic techniques operate on a group of possible solutions within the search space. This approach offers the advantage of finding multiple suitable solutions in a single iteration. These techniques are characterized by their ease of implementation, robustness, and computational performance. [19]By engaging in collaboration and competition, these strategies increase efficiency in identifying optimal solutions when applied to intricate optimization issues such as the ELD problem. If the Emission constraint is added to the conventional ELD problem, then the problem becomes more non-linear. So, the methodology finding of this kind of Problem continues.

The research indicates that any meta-heuristic method employed to address the limitations of traditional optimization methods exhibits weaknesses that hinder its ability to attain the optimal solution. Several drawbacks can be identified in the usual approach. [23]These include the prolonged stagnation of the fitness function at a local optimum, idle individuals in a dead loop, decreased fitness quality across iterations, and slow search space exploration. To address these restrictions more effectively and enhance the efficacy of solutions, several hybrid approaches have emerged that combine two or more soft computing techniques. This approach effectively leveraged a certain methodology's advantages while mitigating its limitations. Several hybrid methods have been widely utilized in addressing the challenges associated with the ELD Problem. These approaches include GA–PSO, ABC–PSO, PSO–GSA, DE-BBO, GA-DE-SQP, and GA-PSO-SQP.

[8]Some notable cons of optimization algorithms are Non-linear objective function and high Dimensionality. Non-convexity, Constraint Handling, Mixed Integer, Multi-objective optimization, Data Uncertainty, Complex Emission Modelling, Real-Time operation, Model Complexity, Scalability, Regulatory and Market constraints, Human factors. To tackle these issues, it is often necessary to employ a blend of sophisticated optimization methodologies, algorithmic enhancements, and interdisciplinary cooperation among professionals specializing in power systems, mathematics, and computer science. Researchers are actively engaged in developing innovative strategies to address these difficulties and enhance the effectiveness and sustainability of power system operations using CEED optimization techniques.

VI. Machine Learning Techniques to EELD Problems

The utilization of machine learning methodologies in collaboration with, or as a substitute for, conventional optimization strategies in the EELD presents numerous benefits and has the potential to tackle various challenges commonly encountered in optimization approaches. [24]Severalbenefits are associated with utilizing machine learning techniques for the EELD.

a. Handling Non-Linearity:[1]Machine learning algorithms, such as neural networks and Support Vector Machines (SVMs), demonstrate exceptional proficiency in capturing complex and non-linear associations among variables. Traditional optimization methods are often less effective in modeling the non-linear cost and emission functions commonly seen in EELD challenges.

b. Data-Driven Solutions:[25] Machine learning utilizes past data to acquire knowledge of patterns and correlations, rendering it highly suitable for CEED challenges that involve the availability of previous data about generator behavior, fuel prices, and emissions. The utilization of a data-driven methodology has the potential to result in models that are more precise and flexible.

c. Flexibility:[26]Machine learning models can effectively adjust to fluctuations within the power system, encompassing factors such as alterations in electricity consumption, fluctuations in fuel prices, and the incorporation of renewable energy sources. The retraining of individuals can enable them to adapt to evolving circumstances, thereby offering adaptability in addressing solutions related to CEED.

d. Incorporating Uncertainty:[27]Machine learning models can integrate probabilistic or uncertainty-based methodologies to accommodate data uncertainty and parameter fluctuations. The implementation of this approach has the potential to improve the resilience and effectiveness of CEED solutions significantly.

e. Multi-objective optimization: Machine learning techniques have a greater capacity to address multi-objective optimization effectively. Decision-makers can efficiently investigate the balance between economic cost and emissions reduction by approximating and modeling the Pareto front.

VII. Conclusion

This study provides a thorough examination of contemporary advanced optimization algorithms that have been developed to address the challenges associated with solving EELD problems. The present study demonstrates the categorization of several optimization approaches and analyses their respective strengths and weaknesses. This paper presents various formulation criteria for the

EELD problem and their significant restrictions. The aim is to provide readers with a comprehensive understanding of the actual CEED Problem. This work primarily concentrates on utilising machine learning techniques to address the multi-objective EELD issue, highlighting the advantages it offers compared to traditional methods.

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