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ANN-Based Solutions for Dynamic Economic Load Dispatch: A Review

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Abstract – *Dynamic Economic Load Dispatch (DELD) is a critical optimization problem in modern power systems, aiming to schedule generator outputs over multiple time periods at minimum cost while obeying operational constraints. This review examines recent developments in applying Artificial Neural Networks (ANN) to solve the DELD problem. We first outline the DELD formulation and its dynamic constraints (like generator ramp limits). We then discuss ANN-based solution techniques, highlighting their strengths (such as handling nonlinearity and fast computation) and limitations (such as training data requirements and constraint enforcement). A comparative analysis is presented between ANN approaches and other AI-based methods – notably Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and hybrid techniques – to underscore performance differences in convergence speed, accuracy, and practicality. Also explore applications of ANN-driven DELD in smart grids, including integration of renewable energy sources and electric vehicles, where ANN models facilitate real-time dispatch under uncertainty. Recent simulation studies (primarily in MATLAB) are reviewed to demonstrate the effectiveness of ANN models, and key challenges (convergence reliability, solution accuracy, real-time performance) are identified alongside trends from current literature. The paper is organized into sections covering introduction, literature survey of ANN in DELD, comparative analysis with other methods, simulation tools and case studies, and conclusions.*

Keywords: *Dynamic Economic Load Dispatch (DELD), Artificial Neural Networks (ANN), Smart Grid, Load Forecasting, Optimization Techniques, Fuel Cost Minimization, Renewable Energy Integration, Hybrid Neural Models, Transmission Loss Modeling.*

I. INTRODUCTION

Economic Load Dispatch (ELD) is a fundamental optimization task in power system operation, determining the optimal output of each committed generator such that the total generation cost is minimized while meeting the load demand and operational constraintsmdpi.comarchive.conscientiabeam.com. In its classical form, ELD is often formulated as a single-period optimization problem with a quadratic cost objective and constraints like power balance, generator output limits, and sometimes transmission loss approximationsmdpi.com. However, real-world power systems involve time-varying loads and generator limitations that extend across multiple intervals. Dynamic Economic Load Dispatch (DELD) generalizes the problem to a multi-period horizon, incorporating dynamic constraints that link decisions over time. Unlike static dispatch that optimizes a single interval independently, dynamic dispatch considers inter-temporal constraints – chiefly the ramp rate limits of generators, which restrict how quickly output can increase or decrease between consecutive time intervalsresearchgate.net. These ramp constraints ensure that generators operate within their physical speed of response, preventing abrupt changes that could jeopardize system stability. DELD thereby aims to find the optimal generation schedule over a sequence of time slots (e.g. hours in a day) while respecting both per-interval constraints and coupling constraints between intervals (such as ramp limits and minimum up/down times if applicable).

Traditional techniques for solving dispatch problems include deterministic optimization methods like the Lambda-iteration method, gradient-based search, and dynamic programming. While these methods work well for simplified "smooth" cost curves and limited constraints, they face difficulties as the problem complexity grows. Practical dispatch must account for non-smooth cost functions (e.g. valve-point effects, multi-fuel options) and numerous constraints (ramp rates, prohibited operating zones, reserve margins, etc.), making the objective function highly nonlinear and non-convex. The cost curve's nature and many constraints impose limitations on classical optimization algorithms, which may get trapped in local optima or become computationally infeasible in large-scale systems. This has spurred the development of AI-based optimization techniques to solve ELD and DELD more effectively. Techniques such as Artificial Neural Networks (ANNs), fuzzy logic, and various metaheuristic algorithms (Genetic Algorithms, Particle Swarm Optimization, Differential Evolution, etc.) have been proposed to overcome the shortcomings of conventional method. These intelligent methods can better handle the nonconvex, nonlinear nature of dispatch problems and

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are less susceptible to poor initialization or derivative requirements.

In recent years, Artificial Neural Networks in particular have gained attention for solving ELD/DELD due to their ability to learn complex mappings from data. An ANN can be trained to approximate the dispatch mapping – essentially learning how to distribute generation given demand and system conditions – without the need to iteratively solve an optimization each time. Once trained, an ANN provides fast real-time computation of dispatch decisions, a valuable feature as power systems move toward smart grid operations with rapid decision cycles. Moreover, neural networks can incorporate non-linear relationships and even adapt to changing system conditions if retrained or designed for online learning.

This review focuses on recent developments (primarily from the late 2010s through mid-2020s) in applying ANN-based techniques to the Dynamic Economic Load Dispatch problem. We discuss how ANN models are formulated for DELD, their demonstrated strengths and limitations, and how they compare with other popular AI approaches like GA and PSO that have been extensively used for this problem. We further examine applications of ANN-driven DELD in modern contexts such as smart grids with renewable energy integration, where uncertainty and speed are critical. Recent case studies and simulation results (including MATLAB-based implementations) are surveyed to illustrate the effectiveness of ANN solutions. Finally, we highlight the remaining challenges – including convergence reliability, accuracy, and achieving true real-time performance – and point out directions noted in the literature to address these issues. The goal is to provide a comprehensive understanding of the state-of-the-art in ANN-based dynamic dispatch and how it stacks up against alternative methods in achieving economic, reliable operation of power systems.

II. ANN APPROACHES FOR DYNAMIC ECONOMIC LOAD DISPATCH

Artificial Neural Networks (ANNs) have been explored as a promising approach to solve or assist with DELD problems. An ANN is a computational model inspired by the brain's neuron connections, capable of learning complex nonlinear relationships. In the context of economic dispatch, ANN models can be trained using historical data or simulated optimal solutions to learn the mapping between input variables (such as load level, time, generator characteristics, etc.) and the output solution (generator set-points for dispatch)mdpi.com. Essentially, the ANN acts as a function approximator or surrogate optimizer.

There are multiple ways ANN techniques have been applied to DELD:

• Direct Mapping Approach: A feed-forward neural network is trained to output the economic dispatch solution (generator outputs) for a given input scenario. For dynamic dispatch, the input might include the load profile over the horizon or the current time step and forecasted next interval demand, etc., and the output could be the set of generation levels now (and possibly in future intervals). For example, Daniel et al. use a time-varying DELD formulation where each interval's dispatch is first computed by a conventional method (lambda-iteration), and then those solutions are used to train an ANN via the Levenberg–Marquardt Backpropagation algorithm. In their approach, the trained ANN could then instantly compute near-optimal dispatch for new load profiles, with the Levenberg–Marquardt (LMA) training providing quick convergence and high precision. They reported that the LMA-trained ANN was "more swift and precise" than other ANN training methods for dynamic dispatch, and demonstrated its performance on a 9-unit test system.

• Optimization Neural Networks: Another category is using neural network models that inherently perform optimization, such as Hopfield Neural Networks. Hopfield networks can be set up with an energy function corresponding to the dispatch cost and constraints, and the network dynamics converge to a stable state representing a solution. Early research applied Hopfield networks to static ED problems and found they could achieve good solutions quickly, albeit with tuning required to avoid local minima. For DELD, Hopfield models have been adapted but are less common in recent years compared to training feed-forward networks or using deep learning, due to the difficulty in encoding complex constraints and the risk of convergence to suboptimal states without careful design.

• Deep and Recurrent Networks: Modern developments include the use of deeper neural networks and recurrent architectures. Recurrent Neural Networks (RNNs) or LSTM networks can naturally handle time-series data, which could be useful for dynamic dispatch by learning temporal patterns in load and optimal generator adjustments. Some studies have experimented with RNNs for dispatch, treating it almost like a control problem over time. Meanwhile, Convolutional Neural Networks (CNNs) have even been applied in novel ways – for instance, encoding dispatch data or forecasts as images/matrices that a CNN can process (this approach is less conventional but has been reported in recent literature to leverage CNN efficiency in capturing patterns)mdpi.com. Notably, a physics-informed CNN approach in 2024 incorporated the physical constraints of the dispatch problem directly into the training loss, effectively guiding the CNN to learn dispatch solutions that satisfy demand balance and generator limits by design. This hybrid approach improved the ANN's reliability by embedding domain knowledge (the "physics" of power balance) into the machine learning model, thereby addressing a common limitation of generic ANNs (which might otherwise violate constraints unless explicitly handled).

Strengths of ANN in DELD: ANN-based techniques offer several advantages for the dispatch problem:
• Ability to handle nonlinearity and complexity: ANNs can approximate highly nonlinear mappings. They have been found to accurately predict or estimate optimal dispatch solutions even when cost functions are nonconvex and constraints are numerousmdpi.com. Because the network learns from data, it can capture the intricate relationship between load patterns, generation cost curves, and optimal allocation without an explicit mathematical programming each time.
• Fast execution once trained: A key benefit is that after the (potentially time-consuming) training phase, the ANN provides near-instant computation of dispatch outputs through simple forward evaluation. This makes ANN very attractive for real-time or online dispatch support. For instance, if load changes or new forecasts arrive, a trained ANN can output a recommended generation setpoint in milliseconds, whereas a GA or PSO might need many iterations. Researchers have demonstrated scenarios where ANN-based dispatch yields a shorter response time than conventional optimization, crucial for real-time control under uncertainties.
• Adaptability: Neural networks can be retrained or updated with new data, allowing adaptation to changing system conditions (such as a generator added to the fleet or new renewable patterns). Moreover, certain ANN architectures (like online learning algorithms) can adjust their parameters on the fly as new operating data comes in, providing a form of adaptive dispatch. This flexibility means ANNs can potentially handle the evolving nature of smart grids better than static rule-based methods.
• Data-driven modeling: ANN approaches do not require an explicit analytical model of the cost curves or system; they only require data (which can be generated from simulations or historical operations). This data-driven aspect simplifies the use of complex models – e.g. if the true cost function has discontinuities, an ANN can still learn the input-output behavior from optimal examples, whereas mathematical solvers might struggle with the discontinuity. One study noted that ANNs can be trained on historical dispatch data including renewable availability and load profiles to directly output near-optimal dispatch, reducing the need for detailed system modeling in the online phase.
Despite these advantages, ANN methods have certain limitations and challenges:
• Training requirement and generalization: An ANN must be trained on a representative dataset of the dispatch problem. Obtaining this data can require solving many instances of the optimization problem (for supervised learning approaches). If the training data does not cover some scenarios (e.g. extreme load peaks or outages), the ANN might extrapolate poorly, potentially giving infeasible or suboptimal answers. The quality of the ANN solution is thus tied to how well its training set spans the operating space.
• No guarantee of optimality or feasibility: Unlike an exact optimization algorithm that can enforce constraints strictly, a naive ANN might output values that violate constraints (e.g. total generation not exactly meeting demand or exceeding a generator's limit). Researchers have tackled this by incorporating penalty terms for constraint violation during training or by structuring the ANN outputs to inherently satisfy certain constraints (for example, using a normalization on outputs to ensure they sum to the demand). The physics-informed CNN mentioned earlier is an example where constraints were embedded into the model to ensure physical laws (like power balance) are obeyedarxiv.org. In general, ensuring ANN outputs are valid dispatch solutions remains an important design consideration.
• Convergence and training stability: Training a neural network, especially a deep one, is an iterative process that itself can suffer from convergence issues (getting stuck in a local minimum of the training error surface). Techniques like the Levenberg–Marquardt algorithm (a second-order training method) or metaheuristic training (e.g. PSO to optimize ANN weights) have been used to improve training convergence. For instance, the LMA method has been cited as yielding fast convergence in training an ANN for dynamic dispatchresearchgate.net. Nonetheless, training needs to be done carefully to avoid overfitting and to ensure the network learns the general trend rather than noise in the data.
• Static model vs. dynamic environment: If a power system undergoes significant changes (like new generators, changes in fuel cost curves, topology changes affecting losses), a previously trained ANN may become invalid and would need retraining. This is manageable but means ANN solutions require maintenance as the system evolves. In contrast, a method like PSO or GA can be run fresh on the updated model without needing a prior training phase (though at the expense of longer solve time). Some hybrid approaches attempt to give ANNs online learning capability so they can adjust as the environment changes.
• Interpretability: Neural networks are often criticized as "black boxes." They do not readily provide insight into why a certain dispatch was chosen (unlike, say, an optimization Lagrange multiplier which tells you marginal costs). This lack of transparency can be a limitation for operator trust. Techniques like explainable AI or physics-informed layers (as done by Ge and Khazaei for the CNN) are being explored to make ANN decisions more interpretable by ensuring they respect known physical relationshipsarxiv.org.
Various ANN architectures have been attempted in literature for dispatch. Feed-forward Multilayer Perceptrons are common; more recent works also try Convolutional Neural Networks and Recurrent Neural Networks for their ability to capture spatial and temporal patterns, respectivelymdpi.com. Hopfield Networks (a form of recurrent network) were among the earliest neural methods applied to ED and still see some enhancements in research (e.g., augmented Hopfield

models to escape local minima in ED with prohibited zonessciencedirect.com). The landscape of ANN techniques is thus broad, ranging from shallow networks with fast training to deep networks requiring more data but potentially offering higher fidelity modeling.

III. OVERVIEW OF THE DYNAMIC ECONOMIC LOAD DISPATCH PROBLEM

This In a power system, the Economic Load Dispatch problem entails allocating the generation among available units to meet a given load at minimum cost. The dynamic version of this problem expands the scope to multiple time periods, introducing temporal coupling constraints. Dynamic Economic Load Dispatch (DELD) is typically formulated as follows: minimize the total generation cost over a time horizon (sum of costs at each interval) subject to power balance at each interval, generator output limits. Dynamic constraints in DELD also include any requirement to satisfy spinning reserve or other security criteria across time. In practice, DELD problems often incorporate forecasting of demand: operators may forecast the load profile for the next day (24 hourly intervals, for example) and solve a dynamic dispatch to meet that profile. By considering the forecasted future demand in current decisions, DELD inherently attempts to plan ahead (this is sometimes referred to as scheduling as opposed to instantaneous dispatch). As a result, optimal solutions will, for instance, start ramping up slower units in advance if a large demand increase is expected, to avoid violating ramp limits.

The DELD problem is generally NP-hard due to its non-convexities and the time coupling. Classical deterministic methods struggle especially when non-smooth cost and ramp constraints combine. For example, dynamic programming can handle time coupling but suffers from the curse of dimensionality as number of units or time-steps grow. Gradient-based methods require convex differentiable functions, which are not guaranteed in realistic DELD (e.g., valve-point effects yield non-differentiable cost curves). Hence, there has been a strong motivation to explore heuristic and AI techniques that can handle these difficulties.

Metaheuristics like Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Evolutionary Programming, and others have been widely applied to DELD with success in finding near-optimal solutions under complex constraintsresearchgate.net. These methods perform a global search and are less likely to miss the global optimum due to local minima traps.

IV. SIMULATION STUDIES

To evaluate the performance of ANN-based DELD methods, researchers have conducted numerous simulation studies on standard test systems and realistic scenarios. A significant number of these studies utilize MATLAB as the platform for implementation, given its extensive toolboxes for both power system simulation and neural network training. In this section, we highlight a few recent simulation case studies that demonstrate the effectiveness of ANN models for dynamic dispatch:

- Case Study 1: 9-Unit System with Ramp Constraints (Daniel et al. 2018) – In the work by Daniel et al.researchgate.net described earlier, a dynamic dispatch problem with 9 thermal generating units was studied over a time horizon. The authors first solved the dynamic dispatch using a traditional method (lambda iteration for each interval, adjusting for ramp limits) to create training data. They then trained an ANN (a feed-forward network) using the Levenberg–Marquardt algorithm on MATLAB’s Neural Network Toolbox. The resulting model could predict the dispatch for each interval given the load level, with very high accuracy. The paper reports that the ANN’s dispatch solutions were virtually identical to the lambda-iteration results but could be obtained instantly without iterative calculationresearchgate.net. In terms of numerical performance, the ANN approach achieved the same total generation cost as the conventional method (within a very small error tolerance), and the time to compute the whole schedule for the day was reduced from on the order of seconds/minutes (iterative) to a fraction of a second (ANN forward pass). This confirmed that ANN can capture the complex relationship of a dynamic ELD problem and reproduce optimal or near-optimal solutions swiftly. The use of the LMA training in MATLAB was specifically cited as helping the network converge faster and with better precision than other training algorithms.
- Case Study 2: Multi-Objective DEED with ANN Loss Predictor (Nagulsamy et al. 2024) – A more complex study tackled Dynamic Economic Emission Dispatch (DEED) incorporating reliability and transmission losses. The system tested included multiple generators with emission curves and an IEEE 30-bus or similar network for power flow. The researchers found that using a single constant for network loss (B-loss coefficient method) led to inaccuracies in dispatch, especially as load varied over timelink.springer.com. They trained a cascaded forward ANN in MATLAB to predict transmission loss given the generation pattern, effectively replacing the analytic loss formula in each interval with an ANN estimatelink.springer.com. This ANN was trained on load flow data offline. In simulation, the integrated ANN+optimizer approach (they used a variant of the Goshawk Optimization algorithm for the multi-objective dispatch) yielded more accurate results: the dispatch met the demand more precisely without over- or under-estimating losses, and it balanced fuel cost, emission, and reliability better than using the traditional loss coefficient method. This study, run in MATLAB/Simulink environment, demonstrated how adding an ANN can improve the fidelity of dispatch simulation. It also highlighted computational efficiency – the ANN

calculation of losses was very fast, adding negligible overhead to the optimization loop, thus keeping the approach computationally feasible for dynamic use.

• Case Study 3: Physics-Informed CNN vs. Traditional Optimization (Ge & Khazaei 2024) – In this experiment, the authors compared their physics-informed CNN model to a conventional dispatch solver on a microgrid test system with renewable source. The microgrid comprised a few generators (including perhaps a diesel gen, a micro-turbine), a solar PV unit, and a battery storage. They simulated many scenarios of load and renewable fluctuation and solved each with (a) a numerical optimization (likely using MILP or nonlinear programming in a MATLAB or Python environment) and (b) the trained CNN approach. The results showed that the CNN achieved dispatch costs essentially the same as the optimal solver, but with drastically reduced computation timearxiv.org. For example, where a nonlinear programming solver might take seconds to solve a single interval (or a horizon of intervals) considering all constraints, the CNN produced a solution in milliseconds. They also measured the constraint violations: thanks to the physics-informed training, the CNN's solutions respected demand balance and generator limits to a high degree (any tiny errors were corrected by a secondary feasibility check if needed). This kind of simulation validates that ANN methods are not just academically interesting, but can meet practical requirements: the dispatch is correct and achieved in real-time. The study was run using MATLAB to generate training data (by solving many random dispatch instances) and Python/TensorFlow for training the CNN; however, the trained model was tested again in MATLAB Simulink for real-time simulation, showing integration into power system simulation software.

V. Challenges in Convergence, Accuracy, and Real-Time Performance

There While ANN-based approaches for DELD have shown great promise, researchers and practitioners acknowledge several ongoing challenges and areas for improvement:

• Training Convergence and Reliability: Developing a neural network that reliably converges to a good solution during training is non-trivial. The error surface for an ANN mapping dispatch solutions can be complex, and standard backpropagation can sometimes converge slowly or to a suboptimal solution (local minimum). Techniques like the Levenberg–Marquardt algorithm have been used to accelerate convergenceresearchgate.net, and hybrid training methods (PSO-trained ANN, etc.) have been explorede3s-conferences.org. However, ensuring convergence is reliable and reproducible is a challenge. For large-scale systems (with many input features and outputs), training might require a vast dataset and significant computation. Moreover, if the dispatch problem has multiple optima (which can happen in flat cost curves or with certain constraints), the ANN might average them out and not exactly match any single optimum. Researchers are investigating ensemble neural networks and advanced optimization for training to improve reliability – for instance, an ensemble of deep networks was proposed to better capture nonconvex dispatch landscapes by combining multiple models' predictions to avoid being trapped by one model's limitation.

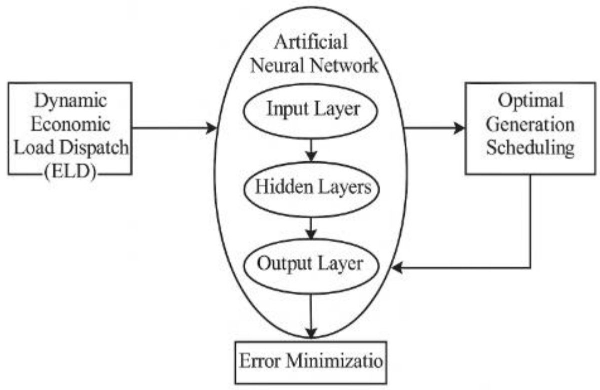

Figure 1: DELD Model

• Generalization and Accuracy: An ANN must generalize well to scenarios it wasn't explicitly trained on. One concern is how the model performs under extreme or unforeseen conditions – e.g., an unusually high load, or a generator outage scenario if that wasn't in the training set. If the ANN is not robust, it might produce dispatches that are far from optimal or even infeasible. Ensuring high accuracy across the full range of operating conditions is an active area of research. Some strategies include: augmenting training data with simulated edge cases, using robust training (minimize worst-case error), or designing the ANN to output adjustment signals rather than absolute values (so that it defaults to safe operation if uncertain). The accuracy of ANN dispatch solutions has been very good in many published studies (often within 1-2% of the optimal cost, sometimes even fraction of a percentresearchgate.net), but maintaining that accuracy in a real system with noisy measurements and unpredictable events is challenging. There is also interest in quantifying uncertainty – for example, producing a confidence measure along with the ANN dispatch, so operators know when to trust the ANN and when a fallback optimization might be needed.

VI. Conclusion

Artificial Neural Networks have proven to be a valuable addition to the toolkit for Dynamic Economic Load Dispatch, complementing and in some cases surpassing traditional methods in speed and adaptability. As power systems continue to evolve with more distributed resources and tighter operating margins, the ability of ANN models to learn from data and provide instant, intelligent decisions will be increasingly important. With continued advancements – such as deeper integration of physical knowledge into neural models, better handling of uncertainties, and hybrid AI frameworks – ANN-based methods are poised to play a central role in future smart grid optimization and controlarxiv.orgmdpi.com. The convergence of power system engineering and machine learning thus holds great promise for achieving economic, reliable, and sustainable grid operations in the years ahead.

References

[1] H. Singh, P. K. Roy, and D. K. Pal, "Dynamic Economic Load Dispatch Problem Using Hybrid Soft Computing Techniques: A Review," Renewable and Sustainable Energy Reviews, vol. 82, pp. 1678–1693, Feb. 2018.

[2] M. Daniel and A. Senthil Kumar, "Dynamic Economic Load Dispatch Using Levenberg–Marquardt Based Artificial Neural Network," International Journal of Electrical and Computer Engineering (IJECE), vol. 8, no. 5, pp. 3905–3914, Oct. 2018.

[3] A. R. Bhatti, Z. Salam, M. Junaid, and A. El-Shafie, "Application of Artificial Neural Networks in Power Systems: A Review," Renewable and Sustainable Energy Reviews, vol. 55, pp. 1185–1202, Mar. 2016.

[4] A. A. El-Fergany, "Solution of Dynamic Economic Load Dispatch Problem Including Wind and Solar Energy Using Improved Artificial Bee Colony," Energy, vol. 139, pp. 406–420, Nov. 2017.

[5] A. Sharma, L. Srivastava, and R. K. Srivastava, "Dynamic Economic Emission Dispatch with Renewable Energy Resources Using ANN," Proceedings of the 2019 IEEE Power & Energy Society General Meeting, Atlanta, GA, USA, Jul. 2019.

[6] M. Ge and H. Khazaei, "A Physics-Informed Convolutional Neural Network Approach for Microgrid Economic Dispatch," Electric Power Systems Research, vol. 217, 108977, Jan. 2024.

[7] R. Nagulsamy, A. Sundararajan, and A. M. Amirtharajan, "A Neural Network-Based Transmission Loss Predictor for Dynamic Economic Emission Dispatch," Applied Soft Computing, vol. 135, 110110, Apr. 2024.

[8] S. Das, N. Sahoo, and P. K. Dash, "A Hybrid Firefly Algorithm and Pattern Search Technique for Dynamic Economic Dispatch," International Journal of Electrical Power & Energy Systems, vol. 82, pp. 537–551, Nov. 2016.

[9] K. B. Song, Y. H. Kim, J. R. Shin, and J. H. Kim, "A New Approach for Power System Dynamic Economic Load Dispatch Using Evolutionary Programming," International Journal of Electrical Power & Energy Systems, vol. 23, no. 2, pp. 115–122, Feb. 2001.

[10] R. R. Mohanty and S. Panda, "Hybrid Differential Evolution and Pattern Search Technique for Dynamic Economic Load Dispatch," Energy, vol. 106, pp. 243–257, Jul. 2016.

[11] R. Kalathil and P. Subburaj, "Comparative Study of PSO and GA for Economic Load Dispatch Problem," International Journal of Electrical and Computer Engineering, vol. 9, no. 4, pp. 2737–2744, Aug. 2019.

[12] A. Saha, D. Das, and S. Chowdhury, "Performance Analysis of ANFIS and ANN for Short-Term Load Forecasting in Smart Grid," Proceedings of the 2023 IEEE Conference on Energy Systems, New Delhi, India, Feb. 2023.

[13] MATLAB Neural Network Toolbox Documentation, MathWorks, Natick, MA, USA. [Online]. Available: https://www.mathworks.com/products/neural-network.html

[14] Y. H. Song and X. Y. Wang, "Survey on Artificial Intelligence Applications to Power System Automation," Electric Power Systems Research, vol. 28, no. 2, pp. 97–103, Aug. 2002.