Artificial Intelligence Based Economic Load Dispatch for Smart Power Systems

Asmit Kumar Pandey
M. Tech. in Electrical Engineering, CBS Group of Institutions, Jhajjar, Haryana.

Nisar
A.P Electrical Department, CBS Group of Institutions, Jhajjar, Haryana.

ABSTRACT

Economic Load Dispatch (ELD) plays a vital role in modern power system operation by determining optimal generation schedules at minimum cost while satisfying system constraints. With increasing electricity demand, renewable energy integration, and complex grid conditions, traditional optimization methods often become insufficient. Recent advancements in artificial intelligence, machine learning, and metaheuristic algorithms have improved ELD performance by enhancing convergence, accuracy, and adaptability. Techniques such as PSO, GA, deep learning, and hybrid optimization support efficient load forecasting and dispatch decisions. Modern ELD also considers emissions, reliability, and sustainability, making it essential for smart grid operation and future energy management.

Keywords: *Economic Load Dispatch, Optimization, Artificial Intelligence, Smart Grid.*

I. INTRODUCTION

Economic Load Dispatch (ELD) is a fundamental optimization problem in modern power system operation, which aims to determine the optimal generation levels of committed power units in order to meet the required electrical demand at minimum operating cost while satisfying a set of system constraints. The concept of ELD has gained significant importance due to the continuous growth in electricity demand, increasing penetration of renewable energy sources, and the need for efficient utilization of generation resources. Traditionally, the ELD problem was solved using classical mathematical techniques such as the lambda iteration method, gradient-based approaches, and linear programming. However, these conventional methods often face limitations when dealing with non-linear, non-convex, and highly constrained power system models. In recent years, the integration of advanced optimization techniques and artificial intelligence-based methods has transformed the way ELD problems are formulated and solved, enabling more accurate, efficient, and computationally feasible solutions for complex power systems. As highlighted in recent studies, the increasing complexity of modern grids requires more adaptive and intelligent approaches that can handle uncertainty, variability, and dynamic load conditions effectively (Zhang et al., 2025; Ma et al., 2025).

The advancement of machine learning and metaheuristic optimization techniques has significantly improved the capability of solving Economic Load Dispatch problems under diverse operating conditions. Metaheuristic algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Ant Colony Optimization (ACO), Whale Optimization Algorithm (WOA), and their hybrid variants have been widely adopted due to their ability to escape local optima and handle multi-dimensional search spaces efficiently. For instance, PSO-based models have been successfully applied in power system optimization due to their fast convergence and simplicity, while hybrid models combining PSO with deep learning techniques have shown improved accuracy in load forecasting and dispatch scheduling (Dai, 2024). Similarly, hybrid intelligent systems integrating Support Vector Regression with optimization algorithms such as Manta Ray Foraging Optimization (MRFO) have demonstrated superior performance in short-term load prediction, which directly supports more efficient economic dispatch decisions (Li et al., 2023). Furthermore, deep learning architectures such as LSTM, Bi-LSTM, and CNN-LSTM have been increasingly incorporated into forecasting frameworks to capture temporal dependencies in load demand, thereby enhancing the reliability of dispatch models (Joobeni et al., 2026). These developments indicate a clear shift from deterministic optimization approaches toward hybrid AI-driven frameworks that provide more robust and scalable solutions for modern power systems.

In addition to forecasting and optimization improvements, recent research has emphasized the importance of integrated and multi-objective approaches in Economic Load Dispatch. Modern power systems are no longer focused solely on cost minimization but also consider environmental impact, emission reduction, energy efficiency, and system reliability. This has led to the development of multi-objective optimization models that simultaneously address economic and environmental goals. For example, distributionally robust optimization (DRO) approaches have been introduced to handle uncertainties in renewable energy generation and load demand, significantly improving system adaptability and reducing operational costs (Ma et al., 2025). Similarly, demand-side management strategies combined with advanced optimization algorithms have been applied to manage electric vehicle (EV) charging loads and reduce peak demand in smart grids (Kumar & Chokkalingam, 2024). In aerospace and industrial applications, load allocation optimization techniques have also been implemented to reduce system weight and improve energy efficiency, demonstrating the wide applicability of ELD concepts beyond traditional power grids (Keleş & Bağrıyanık, 2026). Overall, the evolution of Economic Load Dispatch from classical mathematical programming to intelligent hybrid optimization frameworks reflects the growing need for adaptive, data-driven, and multi-criteria decision-making tools in modern electrical energy systems, ensuring economic efficiency, operational reliability, and sustainable development in future smart grid environments.

II. RESEARCH BACKGROUND

Joobeni et al. (2026) had examined the importance of accurate electric load prediction for optimizing resource allocation and maintaining power grid stability, while noting that the comparative effectiveness of deep learning models across different energy consumption sectors had remained underexplored. The study had proposed a sector-aware framework for medium- to long-term electric load forecasting using monthly data to support strategic infrastructure planning. Five advanced architectures, namely LSTM, BLSTM, Seq2Seq, CNN-LSTM, and Deep LSTM, had been evaluated across the agriculture, industrial, commercial, and residential sectors. Optimal hyperparameters had been identified through exhaustive grid search and validated using a walk-forward approach. A major contribution of the study had been the development of a weighted ensemble model optimized through constrained least-squares minimization, which had been compared with a simple averaging baseline. The findings had indicated that the proposed ensemble model outperformed individual models and the baseline in terms of RMSE, MAE, R^2, and MAPE, achieving an RMSE of 3.43E+08 and an R^2 of 0.9459 on the aggregate dataset. Overall, the study had provided a systematic and effective framework for sector-specific energy management and strategic forecasting.

Eckhoff et al. (2026) had conducted a systematic literature review following PRISMA guidelines to examine hybrid architectures for forecasting sequential electrical load profiles in the context of the global energy transition and increasing electrification. The review had synthesized statistical, machine learning, and deep learning approaches, with particular emphasis on improving predictive accuracy and practical applicability. It had been reported that hybrid models, especially those combining deep learning architectures such as LSTM with optimization techniques like Genetic Algorithm and Particle Swarm Optimization (PSO), demonstrated superior performance in capturing non-linear patterns in load data.

The study had further highlighted that architectures integrating CNN for feature extraction with LSTM for temporal dependency modeling were particularly effective in identifying local trends, cross-correlations, and long-term relationships. A major limitation identified was the absence of a structured framework for handling adaptable output lengths in dynamic neural forecasting, for which the authors had proposed decoupling output-length prediction from core signal prediction. The review had also emphasized that performance evaluation remained overly dependent on MAE, RMSE, and MAPE, and it had recommended the development of application-oriented metrics incorporating economic and planning considerations for more reliable domain-specific validation.

Keleş and Bağrıyanık (2026) examined the growing significance of electrical power systems in aviation, particularly in response to environmental concerns and the increasing replacement of conventional hydraulic, mechanical, and pneumatic subsystems with electrically powered alternatives. The authors observed that, as aircraft became more dependent on electrical energy, system-level optimization for energy efficiency and weight reduction had become essential. Their study specifically addressed the Load Allocation Problem (LAP), which involved determining the most suitable distribution units for supplying electrical loads in order to minimize cable weight, a major contributor to the overall system mass. To solve this problem, they developed an Electrical Power System Planning Strategy (E2P2S) under defined operational constraints. The proposed method was implemented and tested using CPLEX 22.1.0, while the F-16 aircraft platform was employed as a reference case for validation. The findings indicated that optimization significantly reduced cable weight and strongly influenced the overall efficiency of aircraft electrical power systems, thereby underscoring the relevance of such approaches for future electrically intensive aircraft designs.

Bhatnagar et al., (2025) investigated short-term load forecasting (STLF) to predict hourly electricity usage fluctuations, emphasizing the economic benefits of accurate forecasts. They reported the development of various crafted features for three different datasets and their implementation in four models: XGBoost, LightGBM, Bi-LSTM, and Random Forest. The study analyzed the significance of crafted features over basic features using evaluation metrics such as MAE, RMSE, R-squared, and MAPE, and found that prediction accuracy improved markedly when crafted features were employed across all models. Additionally, the authors examined the application of the Polar Bear Optimization (PBO) algorithm for hyperparameter tuning, observing that PBO effectively reduced RMSE, MAE, and MAPE, thereby enhancing model performance. Comparisons with particle swarm optimization (PSO) and genetic algorithm (GA) indicated that GA performed the least effectively, PSO and PBO were comparable for XGBoost, LightGBM, and Random Forest, while PBO significantly outperformed PSO with the Bi-LSTM model, demonstrating its high efficacy for STLF hyperparameter optimization.

Zhang et al. (2025) investigated fluctuations in external energy inputs and internal equipment power consumption in energy supply networks, emphasizing their critical influence on system output stability and the need for advanced optimization strategies in multi-energy systems. They proposed a novel Combined Cooling, Heating, and Power (CCHP) system integrating grid supply, internal combustion engine, gas boiler, lithium bromide absorption chiller, waste heat recovery system, electric chiller, and electric energy storage (EES). Four operation strategies were defined based on load prioritization, considering equipment self-sufficiency and time-of-use tariffs: FPL-H, FPL-C, FHL-P, and FCL-P. To optimize equipment capacity and dispatch strategies, a bi-layer framework using a Particle Swarm Optimization–Gaussian mutation (P-G) algorithm was developed. Their results indicated that the FPL-C strategy yielded the lowest comprehensive economic cost (3471.16 ¥/day) at an optimal EES capacity of 119.26 kW and reduced electricity purchased outside minimum tariff periods by 4.25 %. The study further highlighted that excessive EES capacity or insufficient discharge power could increase total economic costs.

Ma et al. (2025) investigated the challenges in scheduling integrated energy systems (IES) amid rising renewable energy penetration and increasing user demand. They proposed a data-driven distributionally robust optimization (DRO) approach to address source–load uncertainties. Initially, conditional generative adversarial networks (CGAN) were employed to generate scenarios for wind and solar power outputs along with electrical and thermal loads, followed by the application of the K-medoids clustering algorithm to identify typical scenarios. Subsequently, a combined norm, incorporating 1-norm and ∞-norm, was used to constrain these scenarios and construct an uncertainty set. Finally, a two-stage DRO model for an electric–thermal–hydrogen integrated energy system (ETH-IES) was developed. The simulations indicated that the proposed method enhanced system economy, achieving a 2.1% reduction in operating cost relative to traditional robust optimization, while maintaining efficient solution performance.

Kumar and Chokkalingam (2024) examined the rapid growth of the electric vehicle (EV) sector and its implications for power grid management, emphasizing the critical role of Demand Side Management (DSM) in maintaining grid stability while accommodating increased load demand. They developed a DSM algorithm incorporating key objective functions and constraints related to EV load, distributed generation from solar photovoltaic systems, and battery energy storage. Various optimization strategies, including the Bat Optimization Algorithm (BOA), African Vulture Optimization Algorithm (AVOA), Cuckoo Search Algorithm, Chaotic Harris Hawk Optimization (CHHO), Chaotic-based Interactive Autodidact School (CIAS) algorithm, and Slime Mould Algorithm (SMA), were employed to construct these objective functions. The algorithm was simulated using MATLAB/Simulink for multiple load scenarios, such as residential and IT sector loads, and it was observed that peak load reduced from 4.5 MW to 2.6 MW while minimum load increased from 0.5 MW to 1.2 MW, thereby narrowing the peak-to-valley gap. The study also compared the performance of each optimization approach in terms of peak-valley difference, computation time, and convergence rate to determine the best fitness outcome.

Dai (2024) highlighted that with the extensive application of deep learning across multiple domains, power load forecasting, as a critical component of power system operation and planning, faced both new opportunities and challenges. It was noted that traditional forecasting approaches often underperformed under conditions of high uncertainty and load complexity. To address these limitations, the study proposed a PSO-BiTC forecasting model, which integrated a temporal convolutional network (TCN) and a bidirectional long short-term memory network (BiLSTM), with TCN capturing long-sequence temporal features and BiLSTM modeling long- and short-term dependencies. The particle swarm optimization (PSO) algorithm was employed to optimize model parameters, enhancing predictive accuracy and generalization. Experimental findings demonstrated that the PSO-BiTC model outperformed conventional methods, achieving reduced MAE values of 20.18, 17.57, 18.61, and 16.7 across four datasets, alongside lower parameter count and training time. The study was considered significant for improving power system efficiency, optimizing resource allocation, and supporting carbon emission reduction in urban buildings.

Li et al. (2023) examined the increasing significance of demand prediction in electricity management, emphasizing its role in informed decision-making for power systems facing challenges due to high load variability and the integration of renewable energy technologies. They proposed a hybrid approach in which support vector machine parameters were optimized using Manta Ray Foraging Optimization (MRFO) to enhance short-term load forecasting. The study compared the proposed method against five other optimizers—Slime Mould Algorithm, Tug of War Optimization, Moth Flame Optimization, Satin Bowerbird Optimizer, and Fruit-Fly Optimization Algorithm—to assess its relative performance. A case study employing real-world electrical load data was conducted, and various statistical indices were used to evaluate forecasting accuracy. The findings indicated that the hybrid SVR-MRFO method effectively overcame limitations inherent in individual algorithms, achieving high predictive accuracy, with coefficient of determination (R^2) values of 0.999 and 0.993 for training and testing datasets, respectively, demonstrating its superior reliability in short-term load prediction.

Karthik and Kavithamani (2023) examined the development of models for accurately predicting electrical charges, highlighting the importance of long-term electricity forecasting for the strategic management of electrical equipment companies. They noted that short-term forecasts for fuel and unit maintenance had provided essential information for systematically managing day-to-day operations and operational commitments. The study introduced an optimal estimation method (OELF) designed to address microgrid challenges, employing a hybrid convolutional neural network (CNN) and improved whale optimization (IWO) to meet demand and support economic growth. The authors explained that the CNN-IWO algorithm aimed to calculate maximum microgrid demand and optimize controllable load capacities for each test project. They emphasized that careful design of cost and load control strategies was necessary to enhance microgrid performance. Their results indicated that the OELF system demonstrated substantial improvements, with mean MAPE reductions of 7.24%, 6.02%, and 8.27% and mean RMSE reductions of 9.37%, 8.34%, and 5.41% compared to existing fuzzy-based methods for 2-day, 1-day, and 1-hour ahead predictions, respectively.

Lai et al. (2022) investigated the limitations of conventional load forecasting models, which primarily relied on historical data extrapolation and exhibited poor correlation with production information. They developed a production information-based backpropagation neural network (BPNN) hybrid model, integrating genetic algorithm (GA) and particle swarm optimization (PSO), for a papermaking enterprise using three-level electric data. Based on this framework, shift electric consumption quotas and air compressor transformation energy-saving predictions were proposed. Their findings indicated that incorporating production management information improved forecasting accuracy, with the average mean absolute percent error (MAPE) of six forecasting results reaching 1.2%, representing an 18.3% improvement. Additionally, management optimization using shift electric consumption quotas was found to reduce the unit energy consumption of paper products by 3.26%, while energy-saving predictions guided air compressor reforms, resulting in an overall production line power saving of 3%. The study highlighted the high accuracy and practical applicability of the proposed forecasting and energy optimization methods.

III. KEY FINDINGS FROM STUDY

Author (Year)	Objective	Methodology	Optimization / AI Technique	Key Outcome / Findings
Joobeni et al. (2026)	Sector-wise load forecasting for energy planning	Deep learning ensemble framework	LSTM, BLSTM, CNN-LSTM, Deep LSTM + constrained optimization	Ensemble model improved accuracy (R^2 = 0.9459), better than individual models
Eckhoff et al. (2026)	Review of load forecasting models	Systematic literature review (PRISMA)	Hybrid ML-DL models (LSTM + GA/PSO)	Hybrid models improved nonlinear load prediction performance

Keleş & Bağrıyanık (2026)	Optimize aircraft electrical load allocation	Optimization-based system design	CPLEX optimization	Reduced cable weight and improved energy efficiency in aircraft systems
Bhatnagar et al. (2025)	Improve short-term load forecasting accuracy	Feature engineering + ML models	XGBoost, LightGBM, Bi-LSTM + Polar Bear Optimization	PBO reduced MAE, RMSE, and MAPE significantly
Zhang et al. (2025)	Optimize multi-energy CCHP system dispatch	Multi-load energy system optimization	PSO + Gaussian mutation	Reduced operational cost and improved energy utilization
Ma et al. (2025)	Handle uncertainty in integrated energy systems	Distributionally Robust Optimization model	CGAN + K-medoids + DRO	Reduced operating cost by 2.1% with better robustness
Kumar & Chokkalingam (2024)	EV load management via DSM	Smart grid load balancing strategy	BOA, AVOA, PSO, SMA, CHHO	Reduced peak load from 4.5 MW to 2.6 MW
Dai (2024)	Improve deep learning load forecasting	Hybrid deep learning model	PSO-optimized TCN-BiLSTM (BiTC model)	Improved MAE and training efficiency
Li et al. (2023)	Enhance short-term load forecasting accuracy	Hybrid regression-optimization model	SVR + Manta Ray Foraging Optimization	Achieved $R^2 \sim 0.999$ (training), high prediction accuracy
Karthik & Kavithamani (2023)	Optimize microgrid load prediction	Hybrid deep learning optimization model	CNN + Improved Whale Optimization	Reduced RMSE and MAPE in load forecasting
Lai et al. (2022)	Improve industrial load forecasting	Production-based forecasting model	GA + PSO + BPNN hybrid model	Improved MAPE by 18.3%, reduced energy consumption

IV. CONCLUSION

The study of Economic Load Dispatch (ELD) optimization using advanced optimization techniques highlights a significant transformation in the operation and planning of modern power systems. ELD plays a crucial role in minimizing the total generation cost while satisfying system constraints such as power balance, generator capacity limits, ramp rate limits, and transmission losses. Traditionally, classical mathematical methods such as lambda iteration, gradient-based optimization, and linear programming were used to solve ELD problems. However, these approaches often struggled with non-linearity, non-convexity, and complex constraint handling in large-scale power systems. With the rapid evolution of smart grids, renewable energy integration, and dynamic load variations, there has been a paradigm shift toward intelligent optimization methods and hybrid artificial intelligence-based models that provide more efficient, reliable, and scalable solutions for ELD problems. Recent literature strongly supports that metaheuristic and machine learning-based approaches have significantly improved the accuracy, convergence speed, and robustness of load dispatch optimization under uncertain and dynamic conditions (Zhang et al., 2025; Ma et al., 2025). The reviewed studies demonstrate that advanced optimization techniques such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Ant Colony Optimization (ACO), Whale Optimization Algorithm (WOA), and hybrid variants have become highly effective tools in solving complex ELD problems. These algorithms are particularly advantageous because they do not require gradient information and are capable of escaping local optima, making them suitable for non-linear power system optimization. Furthermore, hybrid models combining optimization algorithms with deep learning architectures such as LSTM, Bi-LSTM, CNN-LSTM, and Support Vector Regression have shown superior performance in both load forecasting and dispatch decision-making. Accurate load forecasting plays a critical role in ELD as it directly influences generation scheduling and system cost efficiency. Studies such as Joobeni et al. (2026) and Dai (2024) confirm that deep learning-based forecasting models significantly enhance prediction accuracy, thereby improving the reliability of dispatch decisions. Additionally, optimization-enhanced forecasting models such as PSO-BiTC and SVR-MRFO have demonstrated improved generalization ability and reduced forecasting error, which further strengthens their applicability in real-world power systems (Li et al., 2023). Moreover, recent advancements emphasize multi-objective optimization frameworks that extend beyond cost minimization to include environmental sustainability, emission reduction, and energy efficiency. Distributionally robust optimization (DRO) and stochastic modeling techniques have been introduced to manage uncertainties associated with renewable energy integration and fluctuating demand patterns. These approaches ensure that ELD solutions remain stable and economically efficient even under uncertain operating conditions. Applications in smart grids, electric vehicle load management, and integrated energy systems further demonstrate the versatility of advanced optimization techniques in modern energy infrastructure. Overall, the convergence of artificial intelligence, metaheuristic optimization, and data-driven modeling has revolutionized Economic Load Dispatch by enabling more adaptive, intelligent, and efficient power system operation. The findings of the reviewed literature clearly indicate that future ELD systems will increasingly rely on hybrid intelligent frameworks capable of real-time decision-making, improved computational efficiency, and enhanced sustainability, thereby supporting the development of reliable and cost-effective smart energy systems.

V. FUTURE SCOPE

The future scope of Economic Load Dispatch (ELD) optimization using advanced optimization techniques is highly promising due to the continuous evolution of smart grid technologies, increasing penetration of renewable energy sources, and growing complexity of modern power systems. In future research, one of the most significant directions will be the integration of real-time optimization frameworks capable of handling dynamic load variations and unpredictable generation from renewable energy sources such as solar and wind. Traditional static optimization models will gradually be replaced by adaptive and self-learning systems based on artificial intelligence, particularly reinforcement learning (RL) and deep reinforcement learning (DRL), which can continuously learn optimal dispatch strategies through interaction with the environment. Another important area of development will be the incorporation of hybrid metaheuristic algorithms combined with deep learning models such as transformer networks, graph neural networks (GNN), and long short-term memory (LSTM) variants to improve both forecasting accuracy and dispatch efficiency under highly uncertain conditions. In addition, multi-objective optimization will play a central role in future ELD research, where economic cost minimization will be simultaneously optimized with environmental objectives such as carbon emission reduction, fuel efficiency, and renewable energy maximization. The integration of electric vehicles (EVs), vehicle-to-grid (V2G) systems, and distributed energy resources (DERs) will further increase the complexity of dispatch problems, requiring more advanced optimization frameworks that can manage bidirectional power flow and demand-side participation effectively (Kumar & Chokkalingam, 2024). Furthermore, uncertainty modeling using probabilistic, fuzzy logic, and distributionally robust optimization approaches will become essential for handling variability in load demand and renewable generation. The application of digital twin technology in power systems is also expected to revolutionize ELD by enabling real-time simulation, monitoring, and optimization of entire grid infrastructures. Another emerging direction is the use of quantum-inspired and quantum computing-based optimization techniques, which have the potential to solve large-scale, highly complex ELD problems with significantly reduced computation time compared to classical algorithms. Additionally, cloud-based and edge computing platforms will support decentralized optimization, enabling faster decision-making and improved scalability in smart grid environments. Future studies may also focus on developing lightweight and energy-efficient AI models suitable for embedded systems in power grid controllers. Overall, the future of Economic Load Dispatch lies in the convergence of artificial intelligence, big data analytics, IoT-enabled smart grids, and advanced optimization techniques, which together will ensure more reliable, resilient, sustainable, and economically efficient power system operations.

REFERENCES

1. Joobeni, A. Y., Naghavi, M., Ahmadi, A., & Dashti, R. (2026). A Constrained-Optimization Ensemble of Deep Learning Models for Sector-Specific Electric Load Forecasting. *Results in Engineering*, 110298.
2. Eckhoff, J., Wadhwa, S., Fette, M., Wulfsberg, J. P., & Wanigasekara, C. (2026). Electrical Load Forecasting in the Industrial Sector: A Literature Review of Machine Learning Models and Architectures for Grid Planning. *Energies*, *19*(2), 538.
3. Keleş, O. K., & Bağrıyanık, M. (2026). Load Allocation Optimization in Aircraft Electrical Power System. *Designs*, *10*(2), 32.
4. Bhatnagar, M., Rozinaj, G., & Vargic, R. (2025). Using crafted features and polar bear optimization algorithm for short-term electric load forecast system. *Energy and AI*, *19*, 100470.
5. Zhang, Y., Li, H., Yan, Z., Cao, H., Shi, H., & Jia, Y. (2025). Optimization of energy output in multimodal and multi-load CCHP systems with integrated electric energy storage. *Energy Reports*, *13*, 4734-4748.
6. Ma, M., Long, Z., Liu, X., & Lee, K. Y. (2025). Distributionally robust optimization of electric–thermal–hydrogen integrated energy system considering source–load uncertainty. *Energy*, *316*, 134568.
7. Kumar, M., & Chokkalingam, B. (2024). Demand side management using optimization strategies for efficient electric vehicle load management in modern power grids. *Plos one*, *19*(3), e0300803.
8. Dai, L. (2024). Performance analysis of deep learning-based electric load forecasting model with particle swarm optimization. *Heliyon*, *10*(16).
9. Li, S., Kong, X., Yue, L., Liu, C., Khan, M. A., Yang, Z., & Zhang, H. (2023). Short-term electrical load forecasting using hybrid model of manta ray foraging optimization and support vector regression. *Journal of cleaner production*, *388*, 135856.
10. Karthik, S. S., & Kavithamani, A. (2023). OELF: short term load forecasting for an optimal electrical load forecasting using hybrid whale optimization based convolutional neural network. *Journal of Ambient Intelligence and Humanized Computing*, *14*(6), 7023-7031.
11. Lai, C., Wang, Y., Fan, K., Cai, Q., Ye, Q., Pang, H., & Wu, X. (2022). An improved forecasting model of short-term electric load of papermaking enterprises for production line optimization. *Energy*, *245*, 123225.