

Integrated Explainable Forecasting and Metaheuristic PI Optimization for LFC/AGC

Neha Khurana¹, Chetan Yadav², Gopal Krishan³, Rajesh Kumar^{4*}

Abstract

Since the last decade world has seen a paradigm shift towards alternate sources of energy, due to significant increase in population and ever-rising demand. However, the traditional systems were not designed to cope with these alternate sources and on the other hand these systems are posed with the challenges of efficiency and intermittency. So, it is inevitable that we need to design a system wherein forecasting data has to be studied followed by optimization of AGC for frequency regulation. The forecast, however, could be more accurate if we consider net load forecast in case of renewable energy sources. The present work presents a framework for accurate net load forecasting backed with explainable ai and confirming which variables are playing a crucial role for prediction. For this real time dataset from NASA for temporal dataset, grid India for PSP and VRE dataset surrounding the region of Bhiwani–Hisar–Jhajjar. To overcome the issues posed with the black box ensemble method, Explainability is employed. The explainability SHAP is used for analyzing deeply local and global feature contribution, while individual prediction is performed using LIME based explanations. Then meta heuristic algorithms were analyzed using two area reheat thermal power systems and following algorithm were analyzed and compared ALA, PSO and GA. Considering the attributes peak frequency deviation, settling time, tie-line power fluctuations and integral error indices. From the results it is evident that when the settling time was considered PSO performed the best and had faster response, however improved damping of inter area oscillation is provided by ALA, and when we are looking for balance GA outperformed others.

Keywords: Net load forecasting, explainable artificial intelligence, renewable energy integration, weather informed forecasting, SHAP explainability, Indian power grid.

INTRODUCTION

Accurate forecasting and control of electrical loads and frequencies remain central challenges in modern power systems. Since the earliest surveys of forecasting techniques [1], researchers have emphasized the economic and operational importance of precise short and long-term predictions. Classical approaches, such as regression, exponential smoothing, and time-series models, provided the foundation for early load forecasting [1], whereas systematic reviews have highlighted the growing role of machine learning and artificial intelligence in this domain [2, 3]. More recent scoping reviews have confirmed that deep neural networks, particularly hybrid CNN–LSTM architectures, outperform conventional statistical models in capturing nonlinearities and sequential dependencies in load data [4].

Parallel to forecasting, automatic generation control (AGC) has evolved as a critical ancillary

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service to maintain system frequency and tie-line power within permissible limits in deregulated and renewable-rich environments. Comparative studies of AGC controllers have demonstrated that optimal control, fractional-order PID, and hybrid intelligent schemes can significantly improve dynamic performance over classical PI/PID controllers [5–7]. Hybrid fuzzy-logic and neural approaches have also been proposed to enhance adaptability under uncertain operating conditions [8]. Recent studies have extended these ideas by integrating metaheuristic optimization techniques, such as particle swarm optimization, genetic algorithms, and firefly algorithms, to tune the controller parameters [7–10]. These methods address the limitations of fixed-gain controllers and improve robustness against stochastic loads and renewable fluctuations.

The convergence of forecasting and control research is particularly evident in comprehensive reviews that simultaneously examine wind, solar, and load forecasting [11, 12]. These studies emphasize the coupling between renewable generation and demand response, underscoring the need for integrated approaches that combine predictive accuracy and adaptive frequency regulation. Emerging strategies, such as LSTM-based controllers optimized with genetic algorithms [10], illustrate how data-driven forecasting can be embedded directly into AGC loops to reduce settling times and overshoot in multi-area systems.

Against this backdrop, the present study situates itself at the intersection of forecasting methodologies and advanced AGC controller design. By synthesizing insights from classical surveys [1], systematic reviews [2, 3], and recent intelligent control frameworks [5, 8, 10], we aim to demonstrate how hybrid optimization and machine learning can enhance both the predictive accuracy and dynamic stability of interconnected power systems.

METHOD

In the following work methodology, as shown in Figure 1, a structured pipeline is framed, which constitutes the following.

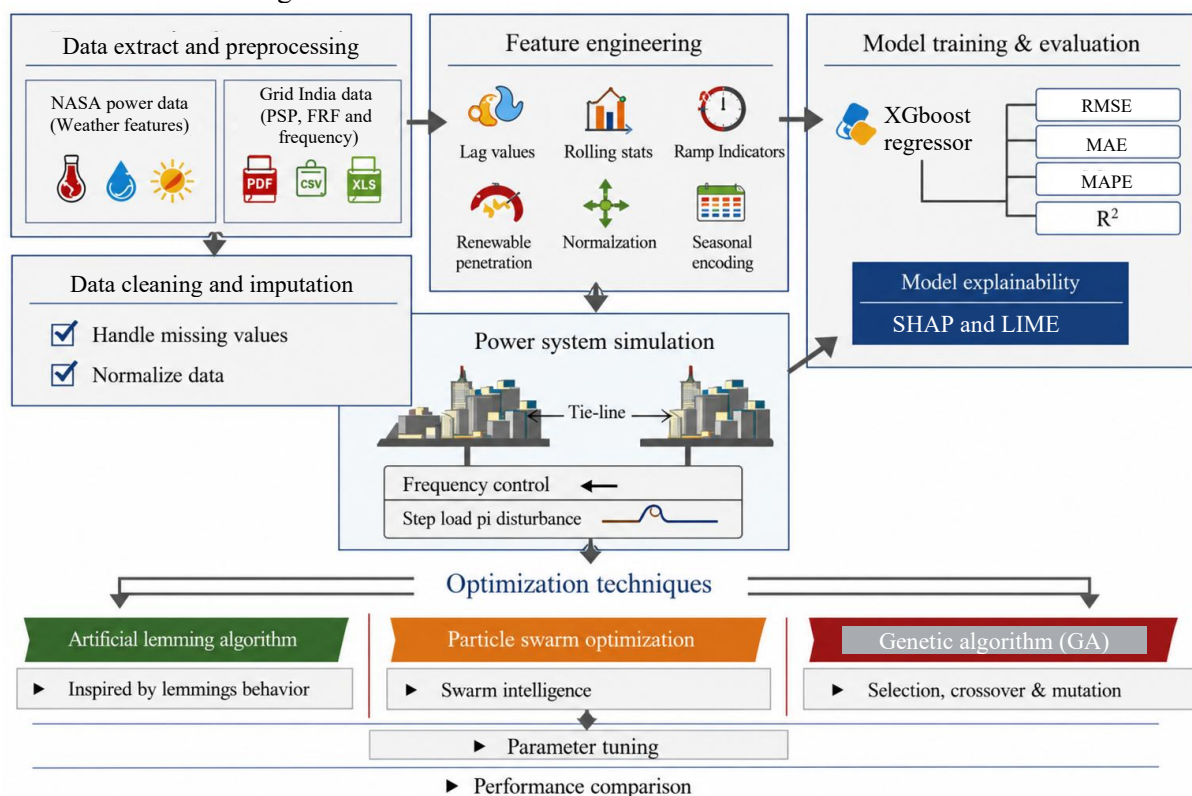


Figure 1. Methodology for implementation of integrated explainable forecasting and metaheuristic PI optimization for LFC/AGC.

Data Extraction

1. Extracting temporal features, including relative humidity, temperature, and all-sky downward irradiance, for the Bhiwani-Hisar Jhajjar region from the NASA power website.
2. Second, the PSP dataset for PSP available on the Grid India website in PDF format. First, the dataset was converted into CSV format with the aid of PDF plumber and tesseract.
3. Similarly, the operation was performed for the VRE dataset available on the Grid India website, and the dataset for the frequency profile was also obtained from Grid India.

Once the dataset was collected, it was since the data was converted from a PDF file, resulting in unstructured data. Therefore, to carry out a meaningful analysis, it is inevitable that the dataset should be preprocessed before proceeding further. Therefore, the dataset was preprocessed by handling the missing values using imputation, filling the missing values with the mean, and filling the categorical variables with forward fill. The final integrated dataset comprised 136 valid data samples within the time span of March–September 2025, and the total number of variables was 35, which included both grid and weather data. After preprocessing, the extracted dataset included 52 features, making it suitable for machine learning operations. With the aid of historical data and creating a window such that there is no information leakage, the following smart features were generated: ag values, rolling stats, ramp indicators, renewable penetration, weather factors, and seasonal encoding. The primary forecasting model used here is the XGBoost regressor, as it has been shown to be the most reliable among various power system forecasting models. The accuracy of the forecasting model was evaluated using the RMSE, MAE, MAPE, and R^2 . Once the model was deployed, the next step was to understand how the decisions were made by these ensemble methods using SHAP and LIME models of explainability.

Once this analysis was performed, we considered two interconnected power systems, wherein each area comprises a speed governor, turbine, generator, and load dynamics. Both areas are connected via a tie line with a system frequency of 50 Hz. With the aid of the net load ramp obtained from the ML-forecasted model, each area was provided with a step load disturbance. This disturbance represents real-world renewable fluctuations. The primary function of Automatic Generation Control (AGC) is to bring the frequency back to 50 Hz, minimize the tie-line power, and settle oscillations faster. Primarily with the aid of PI controllers, the values of K_{p1} , K_{i1} for area 1 and K_{p2} , K_{i2} were optimized. Later, these values were optimized using the Artificial Lemming Algorithm (ALA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA), and the performance of all was noted.

Artificial Lemming Algorithm

This algorithm is a nature-inspired algorithm based on the behavior of lemmings. This algorithm explores and exploits search space. The update equations for this algorithm are

$$X_i^{t+1} = X_i^t + \alpha r(X_{best}^t - X_i^t) + \beta N(0,1)$$

With the help of this algorithm, we can move to the best solution, as it adds randomness in the search space for exploration. This prevents getting caught in local minima. However, the disadvantage is its slow convergence.

Particle Swarm Optimization

The PSO algorithm is inspired by the flocking behavior of birds. In this, every particle finds its pbest and gbest, that is, local and global optima, respectively, which is effective in reducing frequency oscillations during the early transient stages. The search space equation is as follows:

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

Where

ω is the inertia weight

c_1, c_2 are acceleration coefficients

$pbest_i$ and $gbest$ denote local and global optima.

Genetic Algorithm

This algorithm is based on natural selection and comprises three basic operations: selection, crossover, and mutation. The algorithm follows the following steps:

Evaluation of Fitness

1. Selection of best
2. Exchanging materials via crossover
3. And at the end mutation facilitated by random change.

RESULTS AND DISCUSSION

The work carried out previously by the authors in [13] has vindicated that the XG Boost model achieved robust performance from the fact that RMSE was computed close to 0.47 and the value of R^2 was approximately 0.91, as compared to various baseline models, classical regression, persistence, and LSTM. Further, the explainability revealed that the most influential driver of net load variability was the clearness index, followed by ambient temperature and seasonal indicators. However, when we consider the global scale, relative humidity and wind speed contributed less. Although localized LIME explanations highlighted their role during the monsoon months. Further, the forecast-derived ramps were injected into the two-area LFC/AGC model. It is clear from Figure 2 that sluggish recovery and large oscillations, with peak deviations exceeding 0.01 Hz for baseline PI.

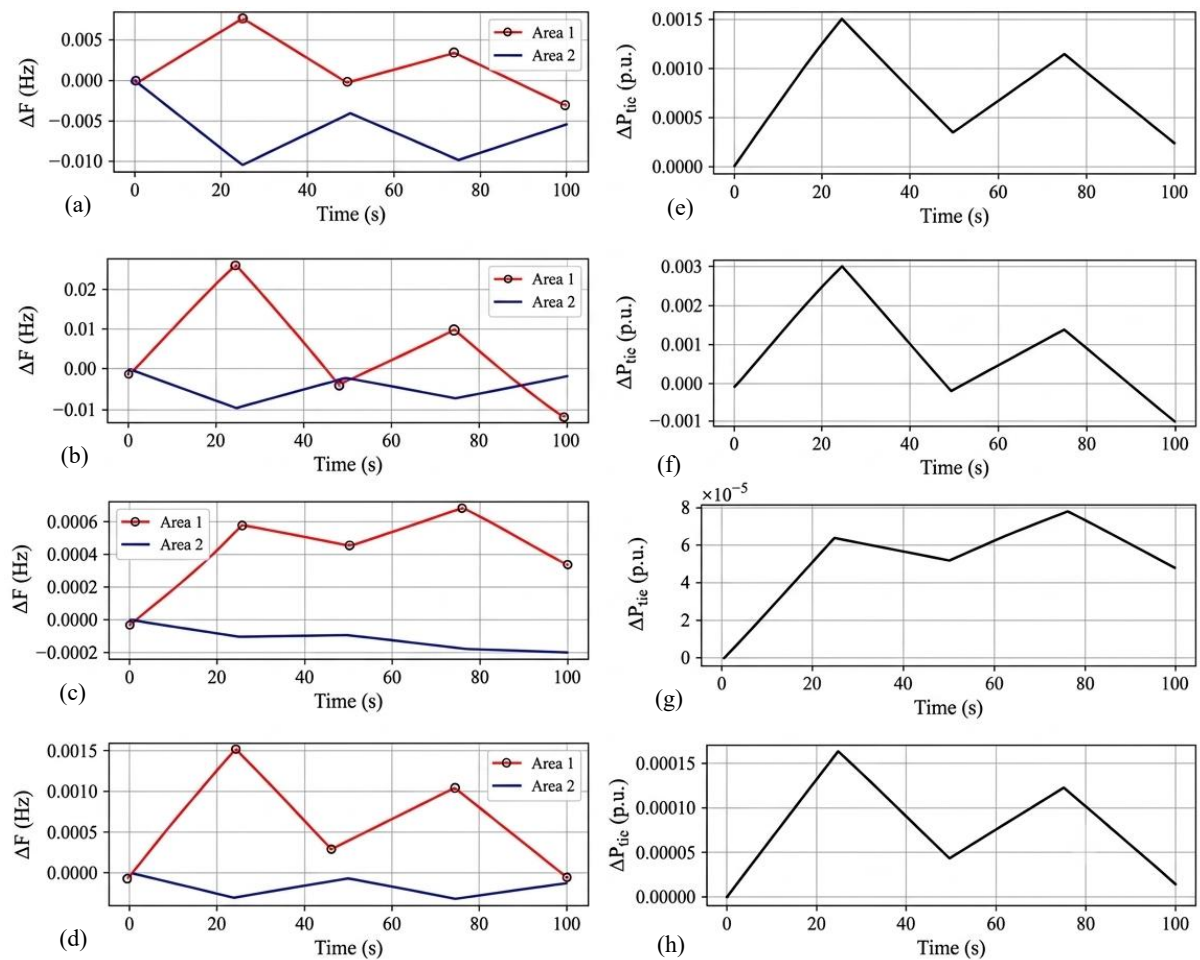


Figure 2. Frequency response and tie line power among various optimization algorithms. (a) Frequency response—baseline PI; (b) Tie-line power—baseline PI; (c) Frequency response—ALA; (d) Tie-line power—ALA; (e) Frequency response—PSO; (f) Tie-line power—PSO; (g) Frequency response—GA; (h) Tie-line power—GA.

However, in the case of ALA, it was observed to improve damping by retaining a moderate overshoot. The most stable responses were obtained by PSO and GA with Δf_1 and Δf_2 settling within 1s and having minimal overshoot (<0.004 Hz). The enhanced inter-area coordination was vindicated by the suppression of tie-line oscillations.

Further error indices (ITAE, IAE, and ISE), as shown in Figure 3, and settling time were computed to determine which metaheuristic algorithm performed well. The results summarized in Table 1 clearly show that the baseline PI produced an ITAE of 73.25, while ALA reduced this value to 19.05. The lowest indices were achieved by the PSO and GA algorithms, with the values of ITAE, IAE, and ISE being 12, 0.37, and 0.0012, respectively, along with faster settling times (<1 s for GA), as shown in Figure 4. Further vindication is provided by the radar chart shown in Figure 5, where GA and PSO form a compact polygon near the origin, indicating optimal performance across all metrics.

Table 1. Performance comparison of controllers.

Controller	Peak Δf_1	Peak Δf_2	Peak ΔP_{tie}	ITAE	IAE	ISE	Settling Time Δf_1 (s)	Settling Time Δf_2 (s)
Baseline PI	0.007700	0.010300	0.001558	0.028600	0.014450	0.000079	4	4
ALA	0.025830	0.009440	0.003053	0.110315	0.053030	0.000924	4	4
PSO	0.000727	0.000192	0.000078	0.005373	0.002280	0.000001	0	0
GA	0.001415	0.000385	0.000155	0.005219	0.002896	0.000003	1	0

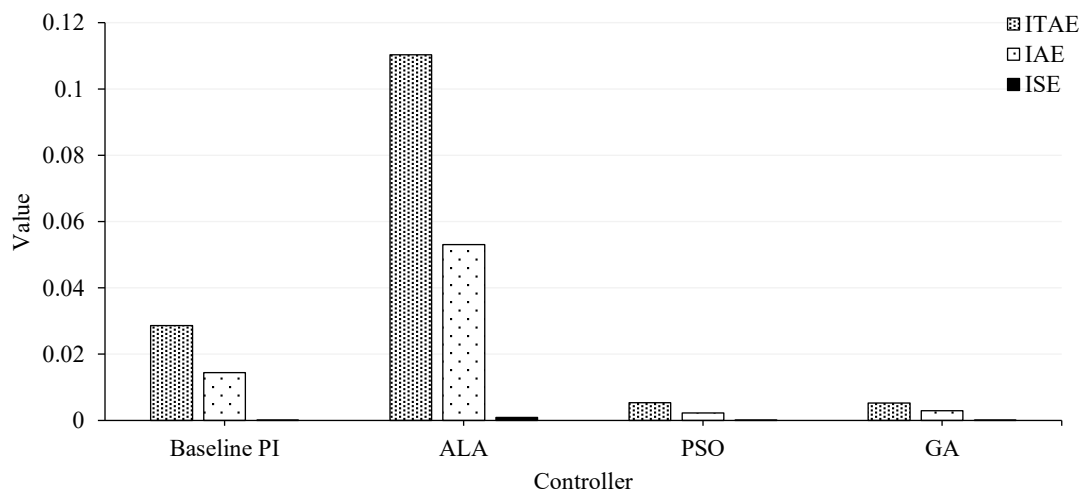


Figure 3. Error indices comparison among various optimizations algorithms.

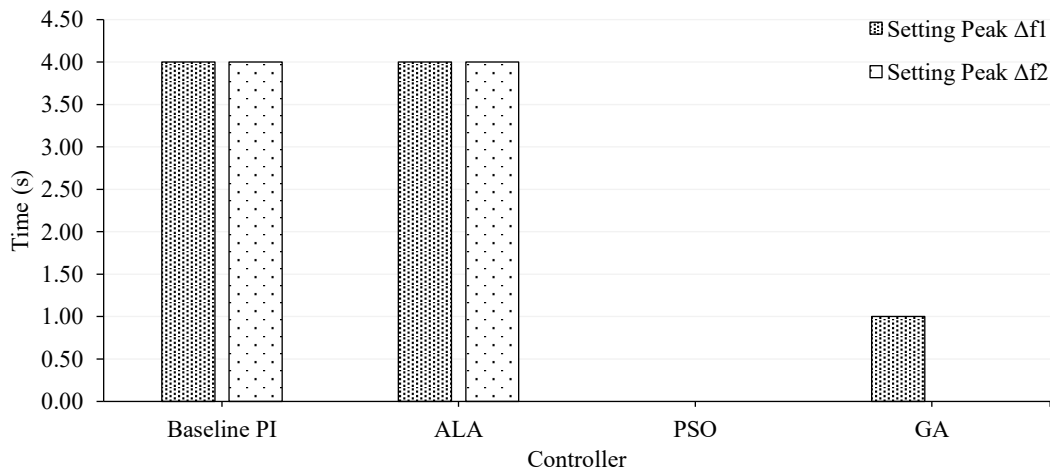


Figure 4. Settling time comparison among various optimization algorithms.

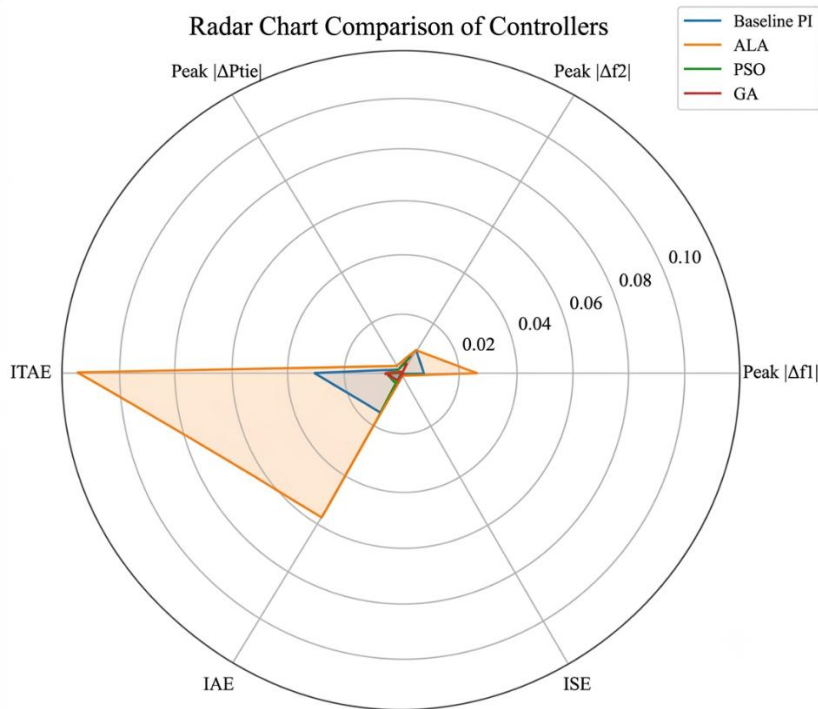


Figure 5. Radar chart comparison of controllers.

By integrating explainability and optimization, this study demonstrates the formation of a closed loop between predictive analytics and dynamic control. Apart from achieving higher accuracy, the forecasting model also provides interpretable drivers, namely the clearness index, temperature, and humidity, that explain ramp behavior. This synergy ensures predictive trustworthiness and dynamic resilience in renewable-rich grids. This dual contribution of explainability for policy and operations and optimization for stability positions the framework as a reproducible and deployable solution for grid operators.

CONCLUSION

This study attempted to establish a coherent bridge between explainable forecasting and optimized dynamic control in renewable-rich Indian grids. In our earlier contribution, the XGBoost-based forecasting framework, augmented with SHAP and LIME, demonstrated that the clearness index and ambient temperature are the most decisive drivers of net-load variability, with humidity and wind speed exerting secondary but context-specific influence. That study vindicated the need for transparent, interpretable models that can guide operators in anticipating renewable-driven ramps.

Building upon these insights, the current study injected forecast-derived ramps into a two-area LFC/AGC model and evaluated the efficacy of metaheuristic optimization for PI controller tuning. The comparative results are unambiguous: conventional PI control is inadequate under renewable disturbances, whereas ALA provides moderate improvement. However, PSO and GA consistently achieved superior performance, with error indices reduced to $ITAE \approx 12$ and settling times below 1 s. Radar chart analysis confirmed their holistic advantage across multiple criteria, underscoring their suitability for real-time AGC applications.

This synergy ensures compliance with evolving grid codes while offering policymakers and system operators a practical toolset for managing renewable-induced variability. Thus, this study advances both methodological transparency and engineering robustness, positioning the framework as a credible solution for the Indian grid transition. Additionally, the suggested architecture improves sustainable renewable integration, scalability, operational dependability, and grid resilience nationwide.

REFERENCES

1. Kuster C, Rezgui Y, Mourshed M. Electrical load forecasting models: a critical systematic review. *Sustain Cities Soc.* 2017;35:257-70.
2. Vanting NB, Ma Z, Jørgensen BN. A scoping review of deep neural networks for electric load forecasting. *Energy Inform.* 2021;4(Suppl 2):49.
3. Wang H, Zhang N, Du E, Yan J, Han S, Liu Y. A comprehensive review for wind, solar, and electrical load forecasting methods. *Glob Energy Interconnect.* 2022;5(1):9-30.
4. Farook S, Sangameswara P. Regular paper feasible AGC controllers to optimize LFC regulation in deregulated power system using evolutionary hybrid genetic firefly algorithm. *J Electr Syst.* 2012;8(4):459-71.
5. Nti IK, Teimeh M, Nyarko-Boateng O, Adekoya AF. Electricity load forecasting: a systematic review. *J Electr Syst Inf Technol.* 2020;7(1):13.
6. Dash R, Reddy KJ, Mohapatra B, Bajaj M, Zaitsev I. An approach for load frequency control enhancement in two-area hydro-wind power systems using LSTM+GA-PID controller with augmented Lagrangian methods. *Sci Rep.* 2025;15(1):1307.
7. Alfares HK, Nazeeruddin M. Electric load forecasting: literature survey and classification of methods. *Int J Syst Sci.* 2002;33(1):23-34.
8. Beichter M, Phipps K, Frysztacki MM, Mikut R, Hagenmeyer V, Ludwig N. Net load forecasting using different aggregation levels. *Energy Inform.* 2022;5(Suppl 1):19.
9. Shayeghi H, Shayanfar HA, Jalili A. LFC design of a deregulated power system with TCPS using PSO. *Int J Electr Electron Eng.* 2009;3(10):632-40.
10. Dahiya P, Mukhija P, Saxena AR, Arya Y. Comparative performance investigation of optimal controller for AGC of electric power generating systems. *Automatika.* 2016;57(4):902-21.
11. Babu VS, Sundar KS. Design of fractional order PID controller for AGC loop in a deregulated power system with RFB and IPFC units. *J Eng Sci Technol.* 2019;14(2):763-83.
12. Falehi AD. Optimal design of fuzzy-AGC based on PSO & RCGA to improve dynamic stability of interconnected multi area power systems. *Int J Autom Comput.* 2020;17(4):599-609.
13. Khurana N, Yadav C, Krishan G, Kumar R. Explainable AI framework for net-load forecasting in renewable-rich Indian grids. In: 2026 3rd International Conference on Advancements and Key Challenges in Green Energy and Computing (AKGEC); 2026 Feb 26-28; Ghaziabad, India. Piscataway (NJ): IEEE; 2026. p. 1-6. doi:10.1109/AKGEC68790.2026.11485825.