



International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 9.935

Volume 15, Issue 10, October 2026

Smart Grid Load Balancing and Demand Forecasting System using Machine Learning

N. Nazmunisha, Chandru M, Vijay Pandiyan K

Assistant Professor, Department of Computer Science and Engineering, K.L.N. College of Engineering, Madurai,
Tamil Nadu, India

U.G. Student, Department of Computer Science and Engineering, K.L.N. College of Engineering, Madurai,
Tamil Nadu, India

U.G. Student, Department of Computer Science and Engineering, K.L.N. College of Engineering, Madurai,
Tamil Nadu, India

ABSTRACT: Electrical grids must continuously balance demand against available supply while avoiding overloads across distribution areas. This paper presents a Smart Grid Load Balancing and Demand Forecasting System that combines short-term machine learning forecasts with rule-based balancing decisions. Historical hourly load data is processed to derive calendar attributes and lag features, which are used by an XGBoost regression model to estimate upcoming demand. The forecast is checked against an operator-defined grid capacity. If predicted demand exceeds the limit, available battery reserve is dispatched first and the remaining deficit is calculated as the load that may need to be shed. A second stage evaluates residential and commercial service areas and transfers available surplus power to the area with higher demand. A Streamlit dashboard presents the forecast, balancing actions and area-wise distribution through interactive Plotly charts. The project demonstrates a decision-support workflow for proactive load management; its current implementation uses historical data and simulation rather than direct control of live grid equipment.

KEYWORDS: Smart grid, Load forecasting, XGBoost, Battery dispatch, Load shedding, Demand balancing.

I. INTRODUCTION

Electrical distribution networks experience changing demand patterns throughout the day and across seasons. When demand rises beyond a safe operating limit, operators must act quickly to maintain reliable service. A purely reactive process can leave little time to prepare for a peak, while fixed threshold-based actions may disconnect more load than necessary. Short-term forecasting can provide an early estimate of demand and help operators evaluate appropriate responses before an overload occurs.

Machine learning models can learn recurring patterns from historical consumption records. In this project, an XGBoost regression model uses calendar information and previous demand values to estimate near-future hourly load. The forecast is connected to a transparent balancing process that prioritises battery support and calculates any remaining deficit. The system also considers two service areas separately so that unused capacity in one area can help reduce pressure in the other.

The implementation is designed as an interactive decision-support dashboard. An operator can configure the safe grid capacity and available battery reserve, and can activate a demand-spike scenario to examine how the system responds. The dashboard visualises the forecast and records the resulting balancing actions. It does not directly operate real substations, batteries or circuit breakers.

The remainder of this paper presents related work, the proposed workflow, the implementation approach, the observed system behaviour and the conclusions. The project report describes the software design and testing in greater detail.

II. LITERATURE REVIEW

Hong and Fan reviewed probabilistic electric load forecasting methods and discussed the value of calendar, weather and lag variables for predicting demand [1]. Chen and Guestrin introduced XGBoost, a scalable gradient-boosting framework suitable for structured prediction tasks [2]. Kong et al. investigated recurrent neural networks for short-term residential load forecasting, demonstrating the relevance of temporal patterns in consumption data [3]. Wang et al. studied neural-network-based short-term power-load forecasting [4].

Research on distributed energy resources also highlights the role of storage in balancing supply and demand. Pudjianto, Ramsay and Strbac discussed the integration of distributed resources and virtual power plants [5]. These studies address important parts of the problem, including forecasting accuracy and resource coordination. The project combines a tree-based forecast with explicit battery dispatch, load-shedding calculations and two-area redistribution in a single interactive prototype.

III. METHODOLOGY

The workflow has four main stages: data preparation, demand prediction, grid-level balancing and area-wise redistribution. The hourly dataset is indexed by timestamp. Features include hour of day, day of week, month, demand 24 hours earlier and demand 168 hours earlier. Rows without the required lag history are removed before training. The data is split chronologically into training and testing portions, and an XGBoost regressor is trained using the engineered features.

Feature engineering is important because electricity consumption follows both recurring calendar patterns and short-term persistence. The hour and weekday variables represent routine activity cycles, while the 24-hour and 168-hour lag values provide reference points from the previous day and previous week. A chronological split is used so that future observations are not used to train the model that is evaluated on earlier observations.

The balancing stage can be expressed as a sequence of transparent rules. Let predicted demand be D , configured safe capacity be C , and available battery reserve be B . If D is no greater than C , no corrective action is required. Otherwise, the initial deficit is $D - C$; battery dispatch is limited to the lesser of the deficit and available reserve, and the remaining deficit is recorded as the load-shedding requirement. This is a simulated decision-support calculation rather than a command sent to physical grid equipment.

At dashboard runtime, the trained model is loaded and used to produce a rolling forecast. An optional peak-demand simulation increases the forecast by 20% to test the balancing logic under a higher-load scenario. For each forecast value above the configured capacity, the algorithm calculates the deficit and uses the available battery reserve first. Any deficit remaining after this dispatch is recorded as the amount of load that would need to be shed. When demand is within capacity, neither action is required.

IV. RESULTS AND DISCUSSION

The prototype brings the forecasting and balancing stages together in a Streamlit dashboard. Its forecast visualisation allows the operator to compare the predicted load profile with the configured capacity. The action log displays battery dispatch and any residual load-shedding requirement for forecast points that exceed the threshold. These values are calculated from the forecast and the capacity and reserve settings supplied by the operator.

Smart Grid Forecasting and Balancing Workflow

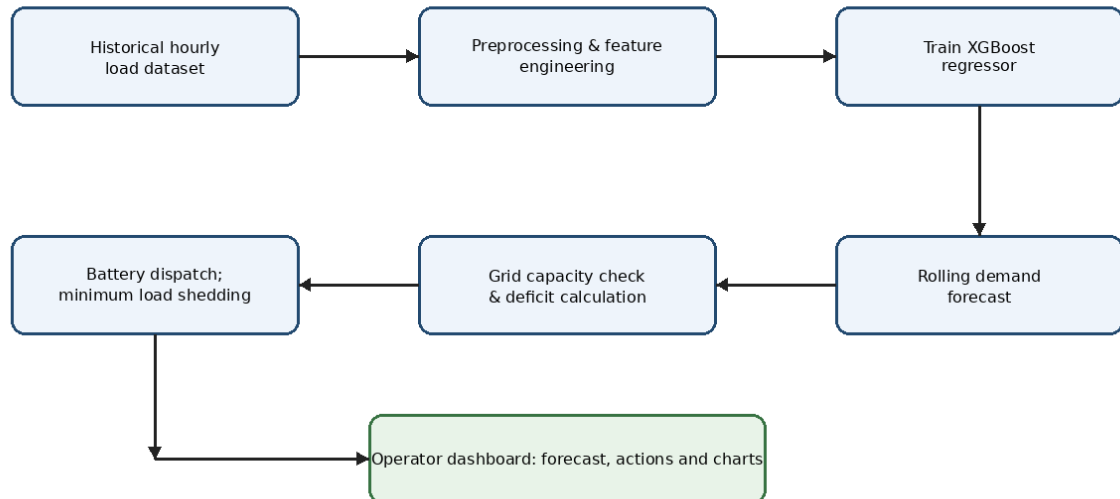


Figure.1. Forecasting and grid-level balancing workflow

Two-Area Load Redistribution Logic

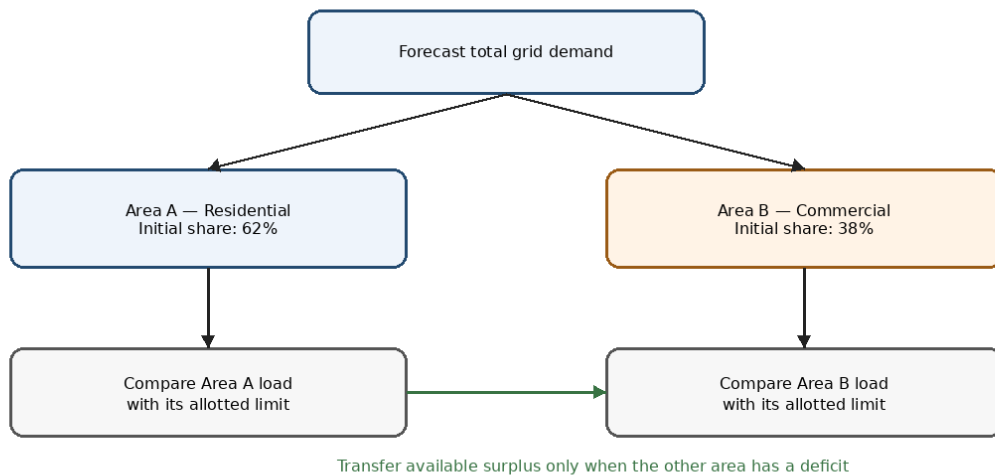


Figure.2. Dashboard outputs and area-wise redistribution concept

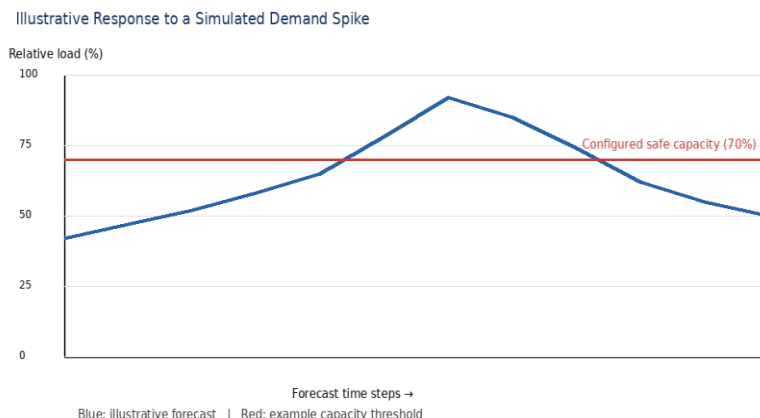


Figure.3. Example balancing response under a simulated demand increase

The area-distribution stage divides total demand between Area A (residential) and Area B (commercial), initially using the 62:38 split specified in the project report. Each area is checked against half of the configured grid capacity. Where one area has a deficit and the other has spare capacity, the algorithm transfers the available surplus, limited by the amount needed to reduce the deficit. The project report describes functional and integration tests for the capacity control, peak simulation, battery dispatch, load shedding and dashboard updates. A numerical MAPE value is not stated here because the report text available for this paper does not provide a verified result to quote.

The diagrams summarise the implemented logic and an illustrative scenario; the scenario chart is conceptual and should not be interpreted as a measured experiment. The current prototype depends on historical input data and a model trained offline. Further evaluation should report verified forecast metrics on a held-out time period and test different demand profiles, battery reserves and capacity thresholds. Practical deployment would also require reliable live telemetry, safety validation and human approval of any operational action.

V. CONCLUSION

This paper presented a smart-grid decision-support prototype that links short-term load forecasting with a transparent balancing strategy. Calendar and lag features are used by an XGBoost model to estimate demand, while the balancing stage prioritises battery reserve and calculates residual load shedding only when needed. A second stage considers demand in residential and commercial areas and transfers available surplus power where possible. The Streamlit dashboard makes the forecast and resulting actions visible to an operator. The current system is a simulation-based prototype using historical data; live telemetry, weather-aware prediction, additional service areas and direct equipment integration remain possible future extensions.

REFERENCES

- [1] T. Hong and S. Fan, "Probabilistic Electric Load Forecasting: A Tutorial Review," *International Journal of Forecasting*, vol. 32, no. 3, 2016.
- [2] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2016.
- [3] W. Kong, Z. Y. Dong, Y. Jia, D. J. Hill, Y. Xu and Y. Zhang, "Short-Term Residential Load Forecasting Based on LSTM Recurrent Neural Network," *IEEE Transactions on Smart Grid*, vol. 10, no. 1, 2019.
- [4] Y. Wang, D. Niu and L. Ji, "Short-Term Power Load Forecasting Based on IVL-BP Neural Network Technology," *Systems Engineering Procedia*, vol. 4, 2012.
- [5] D. Pudjianto, C. Ramsay and G. Strbac, "Virtual Power Plant and System Integration of Distributed Energy Resources," *IET Renewable Power Generation*, vol. 1, no. 1, 2007.
- [6] Streamlit Documentation, "Streamlit API Reference."
- [7] XGBoost Developers, "XGBoost Documentation."



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details