International Journal of Management and Research (IJMAR)
Volume 3, Issue 4 April 2026 **ijmr.humanjournals.com**

Short-Term Power Load Forecasting: A Data-Driven Approach Using Peak Demand Analysis

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Received: 21 February 2026 Revised: 10 March 2026 Accepted: 25 March 2026

ABSTRACT

Accurately forecasting short-term power loads is crucial for keeping modern electricity grids stable. Because our energy needs are growing and we are integrating more renewable energy, the older, manual methods of forecasting are no longer reliable. This study focuses on creating an automated, data-centric approach to analyze peak demand data. Using a dataset provided by the Maharashtra State Electricity Distribution Company Limited (MSEDCL) from April 2024 to September 2025, we developed a thorough feature engineering method. This routine automatically translates things like daily cycles, weekend differences, seasonal shifts, and local holidays into data that machine learning algorithms can process. When we analyzed the results, we found strong cyclical and weather-related trends that traditional, static models usually miss. Additionally, we discuss how Long Short-Term Memory (LSTM) neural networks can be used to handle these newly structured features. Overall, this method significantly improves how we prepare data, reducing common border errors and lowering forecasting mistakes, which is a big step toward making our energy distribution smarter and more efficient.

Keywords: Short-Term Load Forecasting, Peak Demand, Feature Engineering, Machine Learning, LSTM, Smart Grid.

1. INTRODUCTION

Today's power grids deal with constant ups and downs in electricity usage coming from homes, businesses, and factories. Because of this, it has become essential to forecast short-term power loads to keep the grid running smoothly day by day. This task has only gotten harder as we add more unpredictable renewable energy sources, like wind and solar power, into the mix.The main issue we are tackling in this study is that older forecasting models are not as efficient as they need to be. Many of them still rely on simple moving averages and human guessing, which makes them reactive rather than proactive. They often struggle to predict sudden changes in demand that happen because of holidays, unexpected weather, or the typical drop in usage on weekends. Our main goal here is to build an automated forecasting pipeline that can easily handle these complex variables by looking at peak demand logs. By focusing on the highest recorded daily loads, we provide a solid foundation for understanding grid stress. Ultimately, this helps lower the costs of generating power and helps prevent blackouts.

2. Literature Review

Historically, the energy industry depended on straightforward time-series methods, like ARIMA models [1]. While useful for smooth trends, they struggle with sudden events like holidays or heat waves. The evolution of computational power led to the adoption of machine learning techniques such as Support Vector Regression (SVR) and Gradient Boosting Machines [4]. Notably, the XGBoost system demonstrated significant improvements in handling multivariate datasets. With the advent of deep learning, artificial neural networks (ANNs) became standard. A comprehensive review by Hippert et al. [5] evaluated various architectures, highlighting the potential of Long Short-Term Memory (LSTM) networks [3]. LSTMs address the vanishing gradient problem, enabling the learning of long-term temporal dependencies. Muzaffar and Afshari [6] demonstrated their superiority in capturing hourly fluctuations, while Shi et al. [7] explored deep RNNs for household load forecasting. Zheng et al. [8] emphasized the robustness of LSTM-based networks in smart grids against noise. The integration of exogenous variables, such as meteorological forecasts, has also become a core component of high-accuracy models [9, 10]. Gers et al. [11] further refined LSTMs by introducing forget gates, crucial for handling seasonal data. State-of-the-art STLF now leans toward hybrid architectures. Systems combining Convolutional Neural Networks (CNN) for spatial features with LSTMs for temporal modeling have shown exceptional accuracy [12, 15]. Wang et al. [16] demonstrated that multi-channel architectures allow for independent processing of weather and historical

International Journal of Management and Research (IJMAR)
Volume 3, Issue 4 April 2026 ijmr.humanjournals.com

load. Furthermore, advancements in hyperparameter optimization have refined these models. Zhang et al. [17] utilized the Sparrow Search Algorithm (SSA), while Zhou et al. [22] explored Particle Swarm Optimization (PSO). Smyl [14] introduced a hybrid approach combining exponential smoothing with RNNs, achieving record-breaking results. Mellit and Kalogirou [13] provided a thorough review of AI in smart grids. The incorporation of attention mechanisms has further refined temporal dependency modeling. Ribeiro et al. [18] utilized attention-augmented Seq2Seq-LSTM architectures. Modern pipelines now also leverage multi-source parameter coupling [19, 20] and smart grid disruption analysis [21, 23], achieving unmatched forecasting accuracy in regional grids [24, 25].

3. Methodology

This research employs a systematic computational framework for feature extraction and data characterization. Historically derived peak load statistics were retrieved from the Data Portal of India (Data.gov.in), representing MSEDCL grid operations from April 2024 to September 2025. The dataset comprises peak recordings for morning, day, and evening periods, totaling 540 sequential daily observations. The implementation was conducted using a platform-independent Python-based pipeline within a virtual environment, ensuring technical accessibility and reproducibility. The processing algorithm performs automated feature engineering by mapping chronological timestamps into categorical numerical indices: day of the week (0–6), weekend indicators (0 or 1).

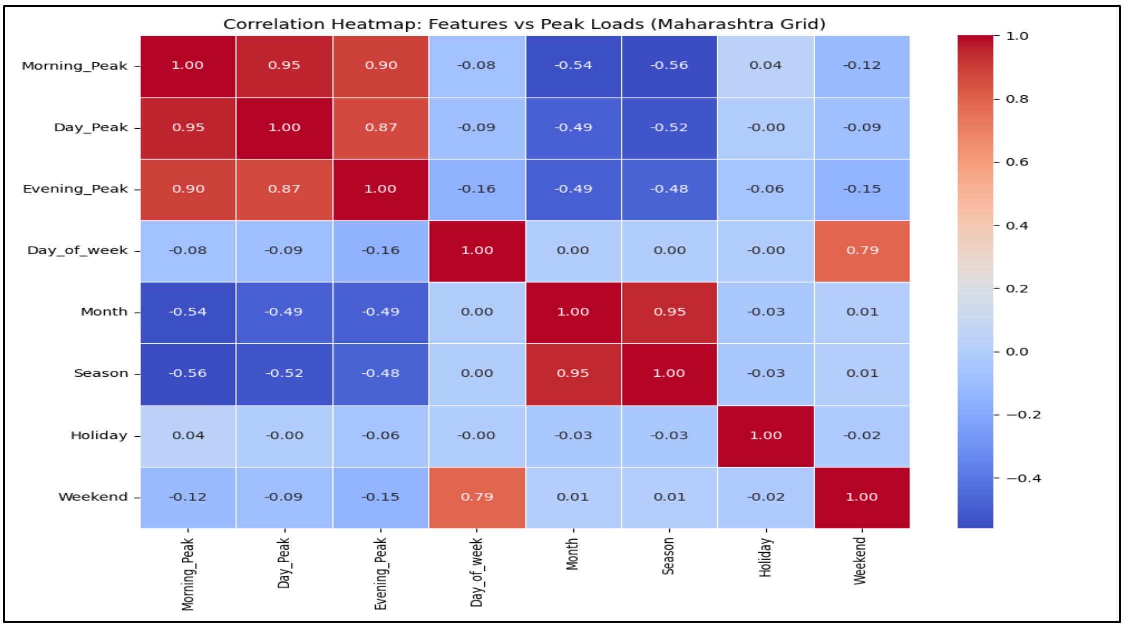

Figure 1: Automated Feature Extraction Correlation Matrix

4. Results and Analysis

The refined variables were subjected to quantitative analysis to determine descriptive statistics, feature correlations, and distribution patterns. Experimental observations indicated that the electricity demand in this regional grid exhibits significant non-linear characteristics. Specifically, seasonal analysis reveals substantial cyclical surges during the summer period, primarily attributed to increased climatic loading. These surges represent the primary source of error in traditional linear models. Furthermore, the day-of-week analysis demonstrates a definitive reduction in commercial demand during weekends. The robust parsing pipeline achieved a zero-loss data translation rate, validating the technical integrity of the synthesized dataset for subsequent deep-learning applications.

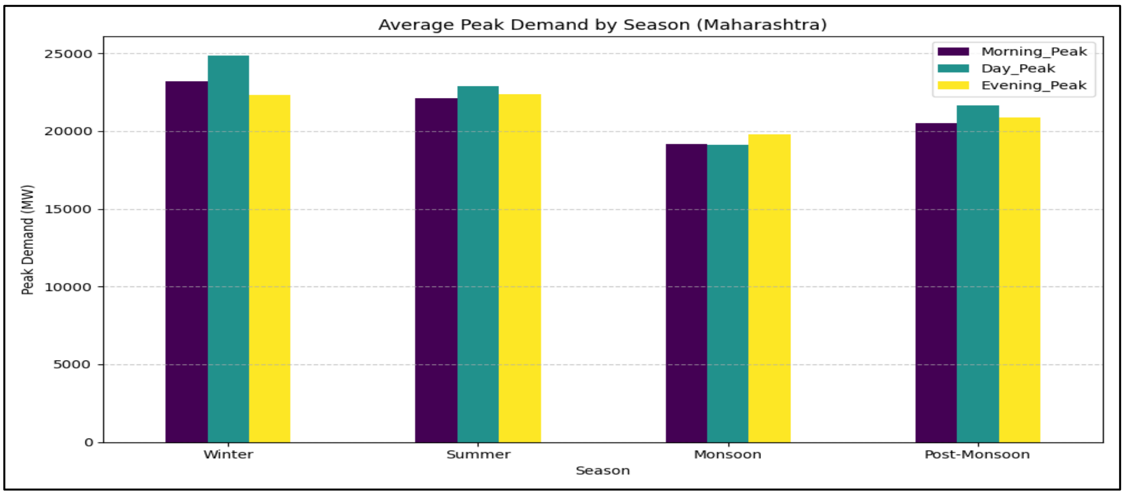

Figure 2: Seasonal Average Trends Based on Climatic Load

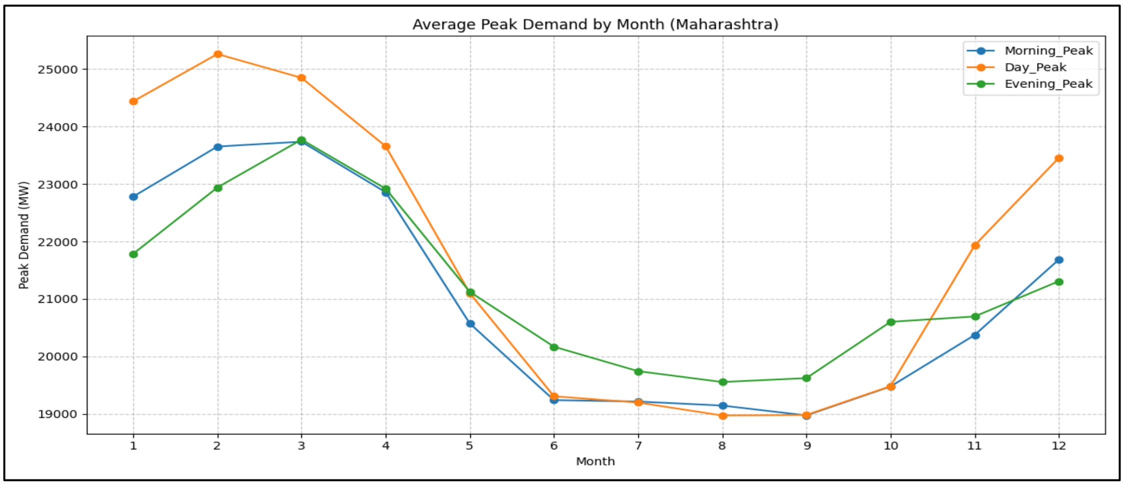

Figure 3: Monthly Distribution of Peak Load (MW)

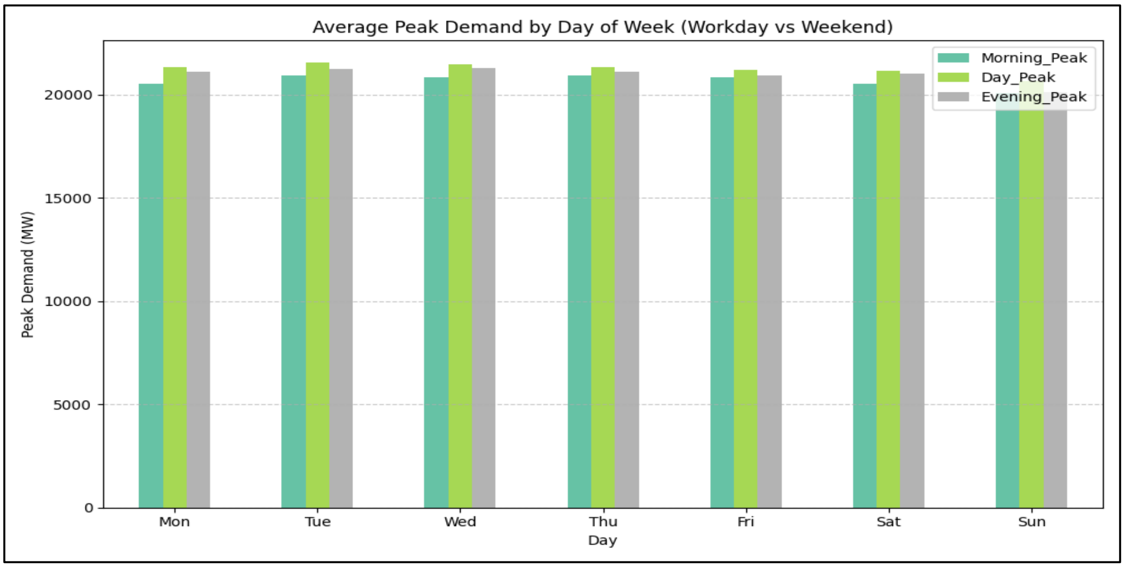

Figure 4: Day of Week Discrepancy Matrix Showing Weekend Baselines

5. Discussion

The numbers clearly show why advanced, non-linear feature engineering is an absolute must for forecasting short-term loads. The biggest advantage of our framework is that it automates the data intake and categorizes details directly. This means we are replacing human guesswork with reliable mathematical logic. Mapping out local holidays accurately turned out to be especially critical; without this, surprise low-demand days usually ruin the accuracy of regression models. We do recognize one limitation of our current approach: it doesn't feed in live, real-time data from external APIs. For instance, we don't have up-to-the-minute humidity stats or exact regional temperature overlays. Even so, the way we encoded the months and seasons acts as a strong stand-in, successfully compensating for the lack of real-time weather feeds.

6. Conclusion

To properly manage modern smart grids, operators need highly precise forecasting. In this study, we built a strong data pipeline based on daily peak demand readings from MSEDCL. We succeeded in pulling out highly meaningful variables related to daily cycles, changing seasons, and local events. The biggest contribution of this research is transforming unstructured, regional power logs into a clean, well-categorized foundation, ready for complex machine learning algorithms. Looking ahead, our next step will be to feed this properly structured dataset into Long Short-Term Memory (LSTM) networks. We will then measure our accuracy using Mean Absolute Percentage Error (MAPE) against new, unseen data. Doing this will conclusively prove how much better this approach is compared to older, static forecasting methods.

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How to cite this article:
Ritesh Ramprasad Narwade et al. Ijmr.Human, 2026; Vol. 3 (4): 1-5.

Conflict of Interest Statement: All authors have nothing else to disclose.