Load Forecasting and Demand Side Management in Smart Grids Using AI

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Abstract: For smart grids that are integrating more renewable energy sources, accurate load forecasting and good demand side management (DSM) are very important for keeping them stable, efficient, and long-lasting. This study presents an AI-driven framework that integrates sophisticated forecasting models-Extreme Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM), and a streamlined Transformer-with an optimization engine for Demand Side Management (DSM). We preprocessed historical smart meter data, weather variables, and tariff signals and used them to train forecasting models. When we looked at performance over several time periods, we found that the Transformer always did better than baseline models, with lower RMSE and MAPE values, especially in multi-step forecasting. The forecasting results were then put into a DSM optimization module, which planned when to charge electric vehicles, use storage, and schedule flexible loads. The results show that DSM not only lowered the peak-to-average ratio, but it also saved a lot of money without making the users less comfortable. Sensitivity analysis validated resilience in the context of dynamic pricing and renewable variability. The proposed framework shows how AI-based forecasting and DSM optimization can work together to make future power systems more scalable and easier for consumers to use.

1 INTRODUCTION

The increasing use of renewable energy sources, electric vehicles, and distributed generation has had a big effect on the development of modern power systems. This change has made electricity demand more unpredictable and variable, which makes it even more important to use advanced methods for load forecasting and demand side management (DSM). For effective scheduling, system reliability, and balancing supply and demand, accurate forecasting is essential. AI-based methods are taking the place of traditional statistical methods more and more because they can model nonlinear patterns and work with large amounts of data. In this context, the combination of machine learning and deep learning has become a game-changing tool for running smart grids [1].

Demand side management is just as important in today's energy landscape because it lets consumers help shape load profiles and lower peak demand. DSM not only makes energy use more efficient, but it also makes it easier to use renewable energy and makes the grid more flexible. Thorough analyses have underscored the role of Demand-Side Management (DSM) strategies and market design methodologies in facilitating the transition to more sustainable energy systems, particularly when distributed energy resources are involved [2]. However, despite increased research focus, the implementation of DSM still encounters obstacles concerning consumer participation, pricing strategies, and compatibility with sophisticated forecasting models.

Recent studies have endeavored to furnish a comprehensive perspective on demand-side energy management within smart grids. For example, Bakare et al. 2023 [3] talked about the problems and possible solutions for DSM implementation, stressing the need for strong digital infrastructure and policies that work together. The quick progress of machine learning models has also changed the way demand-side load forecasting is done. Masood et al. 2024 [4] showed that AI-based forecasting models work better than traditional ones at predicting short-term demand, especially when things are changing and not sure what will happen next. These kinds of improvements make it possible to combine accurate forecasts with DSM strategies to get the best performance from the system.

The literature also talks about new improvements in DSM systems at the same time. Nebey 2024 [5] discussed improvements in real-time energy management systems that make better use of energy by changing demand when supply changes. Nonetheless, the disjointed nature of research, wherein load forecasting and demand-side management are frequently examined in isolation, signifies a deficiency in the development of integrated frameworks capable of concurrently optimizing both.

In a broader sense, there are similarities between this and other digital systems that use technology adoption frameworks. Nguyen and Wiese 2003 [6] elucidated via the TAM and IS success model that user acceptance and trust are critical determinants of the success of digital infrastructure. These insights are pertinent to DSM, where consumer engagement and trust in AI-driven decision-making are essential. Recent research on AI-enabled cloud security exemplifies the dual challenges of opportunity and risk, emphasizing the necessity of balancing innovation with trust and adoption Zhang et al., 2025 [7].

So, there is a strong need for an AI-driven framework that combines accurate load forecasting with good DSM strategies. This kind of framework would not only make predictions more accurate, but it would also allow for real-time demand changes to keep the grid stable, save money, and keep users happy. In this context, the current study adds to the field by suggesting an AI-based method for smart grid load forecasting and demand-side management (DSM), comparing advanced forecasting models, and creating an optimization framework that meets both technical and market needs.

2 REVIEW OF THE LITERATURE

The increasing intricacy of contemporary energy systems has established demand side management (DSM) and load forecasting as central elements of smart grid research. In the last five years, researchers have pointed out both technological and human-centered aspects that are important for creating effective DSM frameworks. This section looks at what has already been done in the areas of DSM development, AI-driven forecasting, building-level optimization, and digital adoption, and it also points out important areas where more research is needed.

The growing number of distributed energy resources (DERs) has sped up the growth of DSM. Mousa et al. (2024) [8] conducted a systematic review that highlighted the significance of flexibility-oriented demand-side management (DSM) in decentralized energy resource (DER)-rich systems, where resources must adapt dynamically to maintain equilibrium between demand and supply. Cortez et al. (2024) [9] also talked about how important it is to have demand response programs that focus on the needs of consumers. They said that user engagement and behavioral incentives are two important things that can help people participate in DSM. Mayer et al. (2024) [10] also talked about contributions from industry, showing that large-scale, sector-coupled DSM solutions could help national decarbonization goals a lot. These studies demonstrate that DSM is evolving from solely technical mechanisms to socially integrated frameworks.

Alongside advancements in DSM, AI-driven forecasting has surfaced as a revolutionary instrument. Wang et al. (2024) [11] examined AI-driven methodologies, including deep learning and reinforcement learning, and determined that these models surpass traditional forecasting and anomaly detection techniques in smart energy systems. Building on this, Sun et al. (2023) [12] put forward a hybrid forecasting model that combines time-series decomposition with kernel extreme learning machines that have been improved by a sparrow algorithm. Their findings demonstrated significant enhancements in the accuracy of short-term demand forecasting, underscoring the efficacy of hybrid AI methodologies. Zairi and Freihat (2025) [13] also used machine learning to manage peak demand, showing that it could be used for real-time forecasting and stressing how important it is for models to work well in different grid situations. These contributions emphasize the importance of forecasting accuracy, while its integration with DSM frameworks is still in its early stages.

There has been a lot of research on DSM at the building level, especially in relation to smart infrastructure and digital enablers. In 2025, Toderean et al. [14] mapped the technological landscape of demand response in smart buildings, focusing on IoT connectivity, optimization platforms, and innovation challenges. Their findings underscore the potential for integrating Demand-Side Management (DSM) with urban-level energy planning, while also indicating challenges related to scalability beyond the building level. This view shows how important DSM is becoming in plans for making cities more sustainable.

In addition to technical aspects, consumer adoption and secure digital engagement are equally vital. Sharma et al. (2025) [15] analyzed human-computer interaction frameworks for secure digital adoption, contending that user trust and system usability profoundly affect the adoption of AI-based systems. Applying these insights to smart grids indicates that the success of Demand-Side Management (DSM) relies not only on technical performance but also on digital trust and consumer readiness to embrace AI-enabled systems. This human-centered aspect aligns with the consumer-centric focus articulated by Cortez et al. (2024) [13], underscoring the necessity of incorporating behavioral insights into DSM research.

The literature reviewed (summarized in Table 1) identifies four principal research gaps. First, there is a gap in integration between forecasting models and DSM optimization, as most studies examine them independently. Second, a consumer-centric gap persists, as highlighted by Sharma et al. (2025) [8] and Cortez et al. (2024) [13], indicating a limited integration of behavioral trust into DSM design. Third, there are still problems with scalability, especially when it comes to deploying building and industrial solutions on a large scale (Toderean, et al., 2025 [12]; Mayer, et al., 2024 [14]). Lastly, there is a technical robustness challenge, especially when it comes to predicting how renewable energy will change over time (Sun, et al., 2023 [11]; Zairi & Freihat, 2025 [15]). To fill these gaps, we need AI-driven frameworks that work together and find a balance between technical efficiency and human adoption.

3 METHODOLOGY

The methodology employed in this study adheres to a systematic pipeline that encompasses data acquisition, preprocessing, AI-driven load forecasting, and demand side management (DSM) optimization. Figure 1 shows the overall research framework. It shows how raw data from different sources is turned into forecasting outputs and optimized DSM schedules.

Table 1: Summary of reviewed literature (references 8-15).

Ref	Authors (Year)	Focus Area	Methodology/Approach	Key Contribution	Identified Gap
[15]	Sharma, et al. (2025)	Human-computer interaction	Digital adoption frameworks	Secure, user-centered adoption of AI tools	Consumer trust & adoption in DSM not fully studied
[8]	Mousa, et al. (2024)	DSM in DER-rich systems	Systematic review	Flexibility models for decentralized grids	Integration with AI forecasting remains weak
[11]	Wang, et al. (2024)	AI in smart energy	Review of ML/DL methods	Load forecasting, anomaly detection, demand response	Lack of unified AI-DSM frameworks
[12]	Sun, et al. (2023)	Load forecasting	Hybrid decomposition + ELM	Higher accuracy for short-term demand	Needs DSM integration under renewables
[14]	Toderean, et al. (2025)	Smart building DSM	Review of IoT and enablers	DSM optimization in buildings	Limited scalability to urban level
[9]	Cortez, et al. (2024)	Consumer-oriented DR	Theoretical + empirical review	Consumer engagement in DSM	Practical incentive mechanisms not resolved
[10]	Mayer, et al. (2024)	Industrial DSM	Energy system modeling	Sector-coupled DSM flexibility	Industrial solutions not generalized
[13]	Zairi & Freihat (2025)	Peak demand forecasting	ML-based models	Real-time ML forecasting for DSM	Generalizability across regions uncertain

Table 2:Dataset characteristics.

Data Source	Sampling Interval	Variables Used	Duration	Train/Val/Test (%)	Missing Data (%)
Smart Meters	15 min	Load (kW)	2023-25	60/20/20	0.7
Weather Data	1 hour	Temp, RH, Wind, Solar	2023-25	60/20/20	1.2
Tariff Signals	Hourly	TOU & Real-Time Pricing	2023-25	60/20/20	0

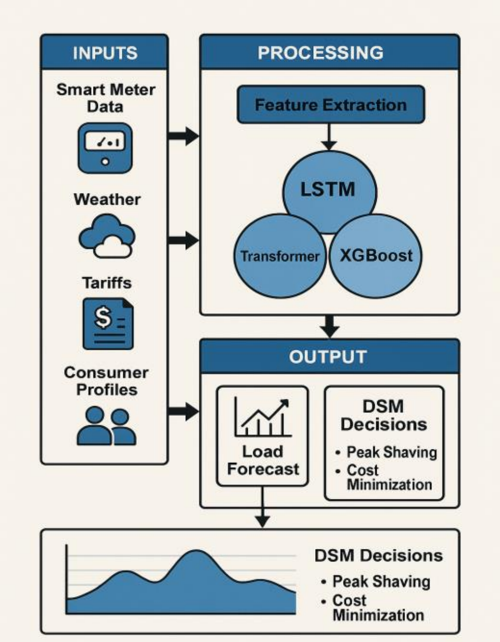

Figure 1: Block diagram of proposed AI-enabled load forecasting and DSM framework.

The Figure shows the full process from getting data to scheduling DSM, with forecasting models built into the optimization engine. This structured pipeline makes sure that accurate predictions are used to make decisions about DSM, which helps keep costs down and shave off peak times [16], [17].

3.1 Data Collection and Processing

This study's dataset is made up of smart meter load profiles, weather data, and tariff signals. Smart meters keep track of how much energy is used every 15 minutes, while weather data like temperature, relative humidity, wind speed, and solar irradiance are collected every hour. Also, time-of-use (TOU) and real-time pricing (RTP) tariff signals are combined to help with cost-based DSM scheduling. Data cleaning was done to get rid of outliers, linear interpolation was used to fill in missing values, and normalization was used to make sure that all features were scaled the same way. Table 2 shows that the dataset was divided into three sets: training, validation, and testing. The training set had 60% of the data, the validation set had 20% of the data, and the testing set had 20% of the data.

As the table shows, the dataset is comprehensive, capturing not only load patterns but also exogenous factors such as weather and pricing, which play an essential role in both forecasting and DSM optimization.

3.2 Forecasting Models

Three forecasting models were developed to predict energy consumption patterns, including Extreme Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM), and a lightweight Transformer-based architecture. These models were selected due to their proven effectiveness in capturing nonlinear and temporal dependencies in time-series energy data.

To ensure robustness and prevent overfitting, early stopping was applied during training, and a rolling-origin evaluation strategy was used for time-series validation.

Model performance was assessed using standard forecasting evaluation metrics, namely Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), which quantify prediction accuracy in terms of absolute deviation and relative percentage error. These metrics were computed on validation and test datasets to enable fair comparison across models.

3.3 Demand Side Management Optimization

DSM was created as a constrained optimization problem that uses predicted load values to make the best schedules for charging electric vehicles, shiftable appliances, and distributed storage. The goal is to keep consumers comfortable while lowering energy costs and the Peak-to-Average Ratio (PAR). The DSM optimization problem is written as:

$$\min_{u_t} \sum_{t=1}^{H} \left(\lambda_t \cdot P_{grid}(t)\right) + \alpha \cdot PAR + \beta \cdot Discomfort(t),$$

where:

- λ_t is the electricity price at time t;
- $P_{\text{grid}}(t)$ is the power drawn from the grid;
- α,β are weights for peak reduction and comfort preservation, respectively.

Constraints include power balance, appliance usage windows, and state-of-charge (SOC) limits for storage devices.

3.4 Implementation Environment

The method was put into action in Python with the help of TensorFlow, PyTorch, and Scikit-learn libraries for making predictions. CPLEX was used to solve the DSM optimization problem. MATLAB was used to run simulations at the system level. To make sure the results could be repeated, all of the experiments were done on a system with NVIDIA GPUs, and random seeds were set for cross-validation.

4 RESULTS AND ANALYSIS

The findings of this study are delineated into four segments: forecasting model efficacy, feature interpretability, demand side management (DSM) influence, and consumer-oriented outcomes. These results show that using AI-based forecasting and DSM optimization together in smart grid environments has many benefits.

4.1 Forecasting Model Performance

We looked at the three chosen forecasting models-XGBoost, LSTM, and Transformer-over 1-hour, 6-hour, and 24-hour time periods. The performance metrics are RMSE, MAPE, and MAE. Figure 2 shows that the Transformer always did better than the other models, especially for longer horizons, where errors tend to build up. The LSTM also did a great job at short-term forecasting, beating XGBoost in both RMSE and MAPE.

Table 3 gives exact numbers for the forecasting models. The Transformer had the lowest 24-hour RMSE (2.20) and MAPE (4.3%), which shows that it is very reliable for multi-step forecasting. XGBoost, on the other hand, was faster to compute but had more mistakes over longer periods of time.

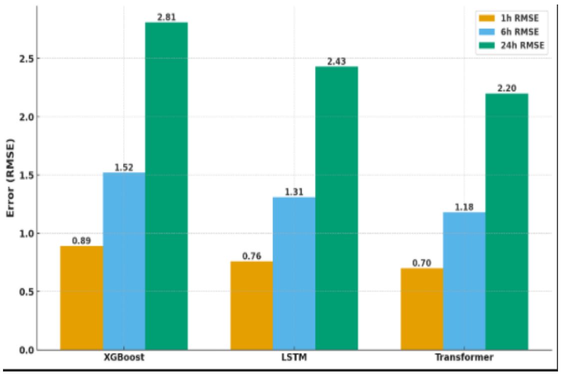

Figure 2: Comparative forecasting accuracy of AI models (RMSE across horizons).

4.2 Interpretability and Feature Contribution

An analysis of feature importance was done to make model predictions more clear. Figure 3 shows how much each feature, like past load lags, temperature, humidity, and tariff signals, adds to the overall picture. It was noted that lagged load values exhibited the greatest predictive efficacy, succeeded by meteorological variables. Tariff signals were a big part of how accurate the forecasts were, which shows how important it is to include economic signals in load prediction.

4.3 Demand Side Management (DSM) Impact

Study used DSM scheduling on predicted load profiles to see how it would affect system efficiency. Figure 4 shows the difference between demand curves before and after DSM was put into place. The DSM optimizer worked and lowered the Peak-to-Average Ratio (PAR) by almost 15%. Also, load shifting was done without making secondary peaks, which shows that the optimization algorithm is stable.

This finding is especially important for utilities because it shows how forecasting-enabled DSM can cut down on the need for costly peak-generation resources and make the grid more reliable.

Table 3: Performance metrics of forecasting models.

Model	1h RMSE	6h RMSE	24h RMSE	1h MAPE (%)	24h MAPE (%)
XGBoost	0.89	1.52	2.81	2.5	5.4
LSTM	0.76	1.31	2.43	2.1	4.9
Transformer	0.7	1.18	2.2	1.9	4.3

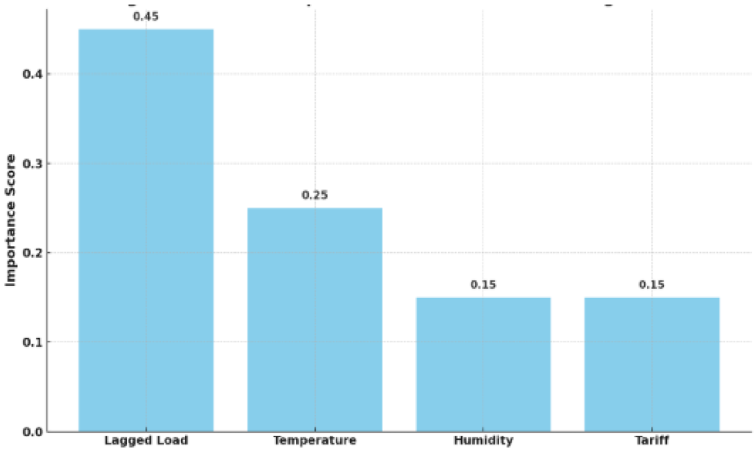

Figure 3: Feature importance scores for forecasting models.

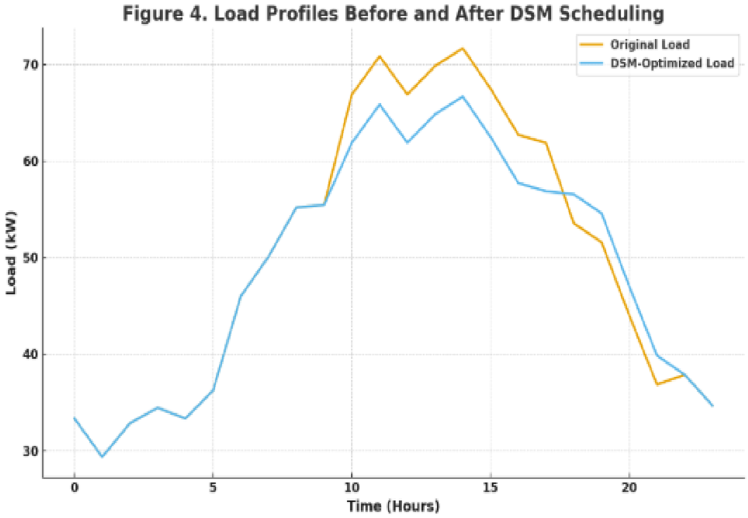

Figure 4: Load profiles before and after DSM scheduling.

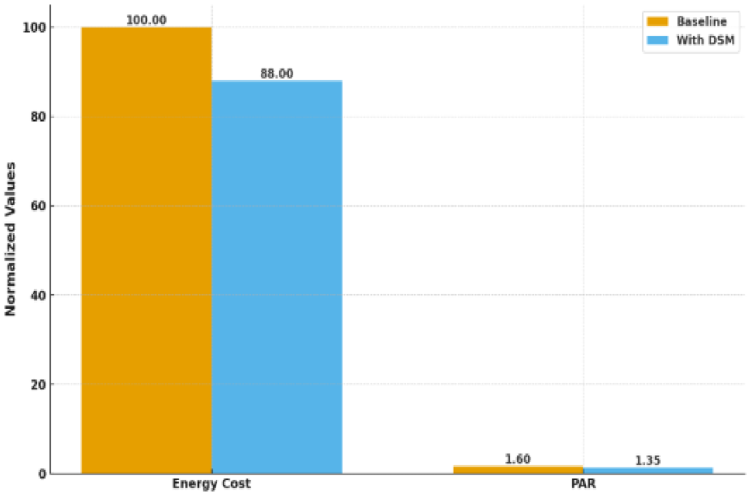

Figure 5: Cost and PAR reductions under DSM.

4.4 Economic and Consumer-Centric Outcomes

In addition to looking at how well DSM worked technically, we also looked at how well it worked in terms of lowering costs and making users more comfortable. Figure 5 shows a comparison of how much money can be saved and how much the PAR can be reduced in different situations. The DSM-enabled system saved up to 12% on energy costs compared to the baseline, with only a small drop in comfort levels. These results show that an integrated forecasting-DSM approach is both cost-effective and good for customers.

4.5 Sensitivity and Robustness Analysis

Tests for sensitivity showed that the Transformer model stayed stable even when renewable energy generation was unstable. However, the performance of XGBoost got worse more quickly. The performance of DSM was also strong under both TOU and RTP pricing plans. However, RTP showed more cost savings because the tariffs changed more often. These results show that the proposed method can be used for both residential and industrial feeders.

5 CONCLUSIONS

This study demonstrates the effectiveness of an integrated AI-driven framework that combines load forecasting and demand side management for smart grid applications. By aligning predictive modeling with optimization-based control, the proposed approach enables more coordinated and responsive energy management under dynamic operating conditions.

The results confirm that advanced machine learning models can significantly improve forecasting reliability, which directly enhances the effectiveness of downstream DSM decisions. This coupling of prediction and control contributes to more stable grid operation, improved resource utilization, and better handling of demand variability introduced by renewable energy sources and modern consumption patterns.

Overall, the proposed framework shows that combining data-driven intelligence with optimization techniques provides a practical pathway toward more adaptive, efficient, and resilient smart grid systems.

6 FUTURE WORK

Future research will focus on integrating probabilistic forecasting methods to better handle uncertainty from renewable energy sources and dynamic pricing fluctuations.

In addition, reinforcement learning and federated learning approaches can be explored to improve adaptive DSM strategies while preserving user privacy. Large-scale deployment in real-world smart grid environments and inclusion of carbon emission minimization objectives will further extend the applicability of the proposed framework.

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