

An Improved Load Forecasting Approach Using LSTM Networks Enhanced by Modeled Demand Response Behavior

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Article Info	ABSTRACT
Article type: Research Article	The increasing penetration of renewable energy sources and the expansion of demand response (DR) programs have introduced considerable uncertainty into electricity consumption patterns, thereby reducing the accuracy of conventional load forecasting models. Most existing forecasting approaches model system load as a single aggregated variable and consequently lack the ability to disentangle and analyze the structural impacts of DR. This paper proposes a load forecasting framework that explicitly and interpretably incorporates DR into the forecasting process. To this end, an index-based DR model (IDRM) is developed to quantify hourly DR using three fundamental indicators—available flexibility, willingness to participate, and participation level—providing a structured and operational representation of DR behavior. The extracted DR component is employed to decompose the observed load and estimate the baseline load, which is then forecasted using an LSTM neural network. The final load forecast is obtained by combining the predicted baseline with the reconstructed DR component. Experimental results based on real-world data demonstrate that the proposed LSTM-IDRM framework reduces the RMSE value by approximately 18.5% (from 0.395 to 0.322) compared with a conventional LSTM model, highlighting the importance of explicit DR modeling in enhancing load forecasting performance.
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NOMENCLATURE			
p_t^{summer}	Power consumption in summer at time t	D	Duration above 70% of peak load [hour]
p_t^{winter}	Power consumption in winter at time t	ρ	financial incentive
μ_t	Winter-to-summer power consumption ratio at time t	α_t	welfare index
$\xi(t)$	available flexibility index	I	correlation coefficient between consumer load and real-time market prices
$C(t)$	flexibility index	L_t	Observed Load at time t
$\Phi(t)$	Willingness to Participate index	t	Index of time $t = \tau, \dots, \tau_t$
B_t	Baseline Load at time t		

I. Introduction

Load forecasting is a fundamental requirement for planning, operation, and market management in modern power systems. In recent years, the structure of electricity networks has undergone a profound transformation driven by the proliferation of emerging loads, the expansion of smart grid infrastructures, the increasing responsiveness of consumers, and the growing dynamics of electricity markets

[1-3]. These developments have significantly intensified demand-side uncertainties and elevated the need for forecasting models that offer both high accuracy and interpretability. Under such conditions, accurate load forecasting becomes essential for ensuring system reliability, optimizing generation schedules, managing market operations, and supporting economically efficient decision-making [4-5].

Among various demand-side developments, demand response (DR) programs have emerged as one of the most influential mechanisms for enhancing flexibility and improving system efficiency. In DR programs, consumers deliberately modify their consumption patterns in response to price signals or operational incentives [6]. Consequently, the observed load no longer reflects only the inherent consumption behavior but represents the actual measured electricity demand, consisting of the baseline demand, i.e., the electricity demand that would have occurred in the absence of DR actions, and the DR-induced behavioral adjustments [7]. This structural complexity transforms the load into a composite signal whose modeling requires explicit consideration of its underlying behavioral components. In many conventional forecasting approaches, the behavioral variations induced by DR are not explicitly modeled and therefore appear as irregular fluctuations in historical data, often degrading forecasting accuracy.

A substantial body of literature has addressed electric load forecasting. Early studies predominantly relied on statistical time-series models such as ARIMA, SARIMA, and ARIMAX [8-10]. While these models provide valuable insights, their ability to capture highly nonlinear relationships is inherently limited. With the advancement of computational techniques, machine-learning methods — including Support Vector Machines (SVM), Random Forests (RF), and gradient-boosting algorithms — gained popularity due to their superior capability in modeling nonlinear dependencies [11-14]. More recently, deep learning approaches, particularly recurrent neural networks and long short-term memory (LSTM) architectures, have demonstrated strong performance by effectively capturing long-term temporal dependencies. Hybrid architectures such as CNN-LSTM have also been proposed to enhance forecasting accuracy under complex operating conditions [15-21]. Despite these advancements, a significant portion of prior research treats the load predominantly as a data-driven signal influenced by historical consumption patterns, meteorological variables, and calendar effects. In DR-active environments, this modeling paradigm becomes insufficient. Behavioral responses to price changes and operational signals are typically embedded implicitly within historical load data and rarely modeled in a structural or distinguishable manner. As a result, DR-induced variations often manifest as unexplained noise, ultimately reducing forecasting accuracy.

In other words, most traditional time-series and deep-learning approaches assume that the load constitutes a single, unified signal and do not distinguish between the baseline component and the DR component. This assumption causes DR-driven adjustments — which are purposeful, price-sensitive, and partially predictable — to be interpreted as noise within the learning process, thereby degrading

forecasting performance, especially in systems with active DR participation. To address this challenge, this paper proposes an integrated and structurally informed framework that explicitly models DR behavior and separates it from the baseline load. The central idea is that the responsive component of demand must be independently extracted, quantified, and modeled to enable accurate baseline forecasting without interference from DR-induced behavioral variations. To this end, an Index-based Demand Response Model (IDRM) is introduced, which characterizes DR behavior using three interpretable indicators:

- Available Flexibility
- Participation Level
- Load Flexibility Index

These indicators provide a structured representation of consumer responsiveness, converting behavioral reactions from an unexplained disturbance into a quantifiable and predictable component. The baseline load, representing the stable consumption pattern, is then forecast using an LSTM network, after which the DR component derived from the IDRM is combined with the baseline prediction to estimate the final system load. The main contributions of this paper are as follows:

1. Development of an interpretable Index-based Demand Response Model (IDRM) for quantifying consumer DR behavior: The proposed model characterizes hourly demand response behavior using three meaningful indicators, including available flexibility, willingness to participate, and participation level. Unlike conventional approaches that represent DR as an aggregated variation or an implicit effect within the load profile, IDRM provides a structured and measurable representation of DR behavior.

2. Development of an IDRM-based forecasting strategy that explicitly incorporates demand response behavior into the forecasting process: The proposed strategy first estimates and removes the DR component from the observed load to obtain the baseline load, forecasts the baseline load, and subsequently estimates and reintegrates the corresponding DR component to reconstruct the final load profile. This sequential structure enables the forecasting model to focus on the underlying consumption pattern while preserving the impact of demand response in the final prediction.

3. Establishment of a model-independent forecasting framework: The proposed framework can be integrated with different forecasting architectures without modifying their internal structures. Its applicability is evaluated using ARIMA, LSTM, CNN, and AT-LSTM, and the consistent reduction in forecasting errors demonstrates that the proposed IDRM-based strategy is not restricted to a specific forecasting algorithm and can serve as a general approach for improving short-term load forecasting accuracy.

The remainder of the paper is organized as follows: Section II introduces the IDRMM and details the derivation of behavioral indicators. Section III presents the methodology for computing the DR signal. Section IV describes the proposed two-stage forecasting framework. Section V provides numerical results and performance evaluation, and Section VI concludes the paper with key findings and future research directions.

II. Index based Demand Response Model

The proposed approach considers residential consumers equipped with electric cooling systems, while electric heating loads are not included in the modeling framework. Accordingly, the temperature-sensitive component of electricity consumption considered in this study is primarily associated with cooling loads. This assumption provides the basis for defining the welfare index and the subsequent behavioral indicators.

Analyzing the load curves of a single consumer or a group of residential consumers makes it possible to identify the seasonal effects of cooling equipment on consumption patterns. The difference between load curves on hot and cold days reflects both the intensity of cooling equipment usage and the associated comfort levels of consumers. A larger difference indicates greater utilization of cooling devices, corresponding to a higher degree of consumer comfort. To quantify this relationship, a welfare index for each consumer group is calculated using the following formula:

$$\begin{aligned} \alpha_t &= \frac{\bar{p}_t^{summer} - \bar{p}_t^{winter}}{\bar{p}_t^{summer}} \\ &= 1 \\ &\quad - \frac{\bar{p}_t^{winter}}{\bar{p}_t^{summer}} \\ &= 1 - \mu_t \end{aligned} \quad (1)$$

According to Equation (1), during summer, a value of closer to 1 indicates a lower comfort-seeking tendency for the studied group, as they have refrained from using cooling systems. Conversely, a value closer to 0 signifies a higher comfort-seeking tendency, reflecting a greater reliance on cooling equipment. In other words:

$$\begin{aligned} IF \mu_t \rightarrow 1 THEN \xi &\rightarrow 0 \\ IF \mu_t \rightarrow 0 THEN \xi &\rightarrow 1 \end{aligned} \quad (2)$$

According to Equation (2), the available flexibility is inversely proportional to the ratio of winter-to-summer power consumption. In other words, as μ_t approaches zero, the available flexibility increases, and vice versa. Therefore, the available flexibility index is defined as follows:

$$\xi_t \approx [1 - \exp(-D * \alpha_t^2)] \quad (3)$$

In Equation (3), ξ_t represents the available flexibility and D represents the duration of high-load consumption and is expressed in hours. It is calculated directly from the historical load profile as the total duration during which the load remains above 70% of its daily peak value. The parameter (D) is introduced to distinguish consumers with similar peak demand but different persistence of high consumption. For example, two consumers may have the same peak load, while one maintains a high consumption level for a shorter period and the other maintains it for a longer period. Therefore, (D) provides additional information about consumption behavior and comfort-seeking tendency. Since (D) represents a duration rather than a discrete count, it can take continuous values when load data are available at sub-hourly resolutions. In general, ($0 < D < 24$) hours. A threshold of 70% of the daily peak load is adopted as an empirical threshold for identifying periods of sustained high consumption. The value of (D) is directly obtained from the historical load data and is not estimated through regression or optimization.

The squared term μ_t^2 is introduced to capture the nonlinear response of consumers to changes in thermal conditions. Small deviations in temperature may result in limited changes in thermal dissatisfaction and, consequently, in the use of cooling equipment, whereas larger deviations from the thermal comfort range may lead to a more pronounced response. As illustrated in Figure 1, thermal dissatisfaction increases nonlinearly as temperature deviates from the comfort zone. Therefore, μ_t^2 is adopted as a moderate nonlinear transformation to capture the increasing sensitivity of consumer behavior to larger thermal deviations.

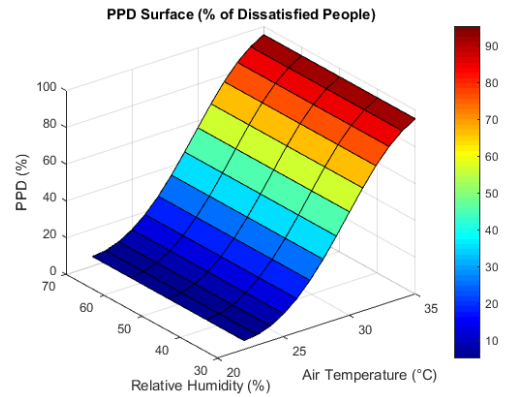


Figure 1: Percentage of individuals dissatisfied with thermal conditions according to ASHRAE Standard 55

According to ASHRAE Standard 55, variations in ambient temperature affect the thermal comfort conditions of occupants and consequently the percentage of individuals dissatisfied with their thermal environment. Figure 1 is derived from the relationship for the percentage of people dissatisfied with thermal conditions presented in ASHRAE Standard 55 and illustrates that thermal dissatisfaction generally increases with increasing temperature. Greater

thermal discomfort is also generally associated with increased use of cooling equipment. Therefore, electricity consumption associated with cooling equipment can reflect consumers' responses to changes in thermal conditions in the load profile. From this perspective, the general pattern of cooling-related electricity consumption can be interpreted within the relationship between thermal conditions and occupant comfort described by ASHRAE Standard 55.

However, consumer electricity consumption and willingness to participate in demand response (DR) programs are not determined solely by thermal conditions. Other factors, particularly the financial incentives offered by the aggregator and the relationship between electricity prices and consumer load patterns, can also influence participation behavior. For example, a higher financial incentive can increase the attractiveness of participation, while the effectiveness of a price-related incentive depends, in part, on the extent to which the consumer's high-load periods coincide with periods of high electricity prices. Therefore, to represent the consumer's willingness to participate in DR while considering both thermal and economic factors, the following formulation is proposed:

$$\Phi_t \approx \rho * \exp(-D * I * \alpha_t^2) \quad (4)$$

Φ_t , represents the willingness-to-participate index at time t , ρ represents the financial incentive factor offered by the aggregator and I represents the correlation between the consumer's load pattern and the electricity-price signal.

The parameter ρ is a dimensionless financial incentive factor. A value of $\rho=1$ represents the reference payment, whereas, for example, $\rho=1.20$ represents a 20% increase over the reference payment. The parameter I represents the correlation between the consumer's load pattern and the corresponding electricity-price signal. In the general formulation, different values of I can represent different degrees of alignment between load and price. In the numerical analysis of this study, $I=1$ is assumed, corresponding to the case in which the load peak is fully aligned with the peak-price period.

This formulation provides a quantitative representation of the effect of thermal conditions and economic incentives on consumers' willingness to participate in DR programs. Once the willingness-to-participate index and the available flexibility are determined, the overall participation level can subsequently be calculated as described in the following formulation.

Once the available flexibility index and the willingness-to-participate index have been determined, the overall flexibility index is defined as the product of these two indices. This formulation reflects the fact that the availability of flexible load alone does not necessarily imply effective participation in a DR program. Similarly, a high willingness to participate cannot result in substantial DR if sufficient load flexibility is not available. Therefore, the overall

flexibility index simultaneously accounts for both the physical availability of flexible consumption and the consumer's willingness to provide DR. It is expressed as follows:

$$\begin{aligned} C_t &= \xi_t * \Phi_t \\ &= [1 - \exp(-D * \alpha_t^2)] * [\rho * \exp(-D * I * \alpha_t^2)] \end{aligned} \quad (5)$$

where C_t , denotes the flexibility index at time t .

The flexibility index C_t is a dimensionless quantity that represents the fraction of the observed load considered flexible at time t . To convert this behavioral index into a physical DR signal, the DR component is obtained as:

$$DR_t = C(t) * L_t \quad (6)$$

where DR_t denotes the physical DR component at time t , expressed in kW or MW, and L_t denotes the observed load at the same time.

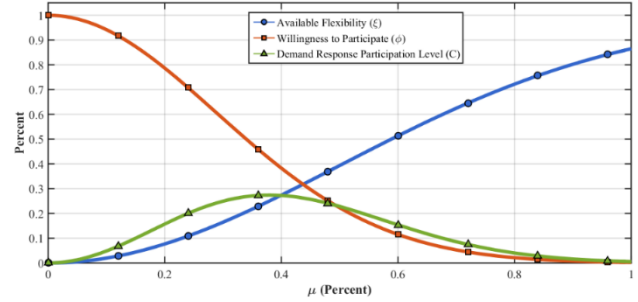


Figure 2. Relationship between proposed indexes.

As illustrated in Figure 2, available flexibility increases as electricity consumption from active cooling equipment rises. Conversely, consumer willingness to participate in demand response (DR) programs declines as thermal discomfort increases. At low temperatures, when cooling systems are inactive, available flexibility is low, yet willingness to participate is high. Conversely, at high temperatures, active cooling creates high flexibility, but willingness drops significantly. In both scenarios, the effective DR potential remains limited because one of the two components required to provide DR is insufficient. The interaction between these two indicators is therefore reflected in the overall flexibility index C_t , which determines the fraction of the observed load that can be considered flexible at each time step.

While IDRMs provide the structural and behavioral modeling components, their integration into the forecasting process is described in the next section.

III. Forecasting Framework

This section presents the complete forecasting framework, which integrates behavioral decomposition, baseline prediction, and final load reconstruction. The workflow is summarized in Figure 3, and each stage is described in detail in the following subsections.

It should be emphasized that the proposed framework does not directly use demand response (DR) information as an

input to the LSTM model. Instead, DR behavior is explicitly incorporated through a decomposition–reconstruction strategy. First, the IDRM estimates the hourly DR component and separates it from the observed load to obtain the baseline load. The LSTM is then trained to forecast only the baseline load, which represents the intrinsic consumption pattern without DR-induced fluctuations. Finally, the reconstructed DR component is added to the predicted baseline load to obtain the final load forecast. This strategy enables the forecasting model to learn the underlying load dynamics while explicitly accounting for the behavioral effects of demand response.

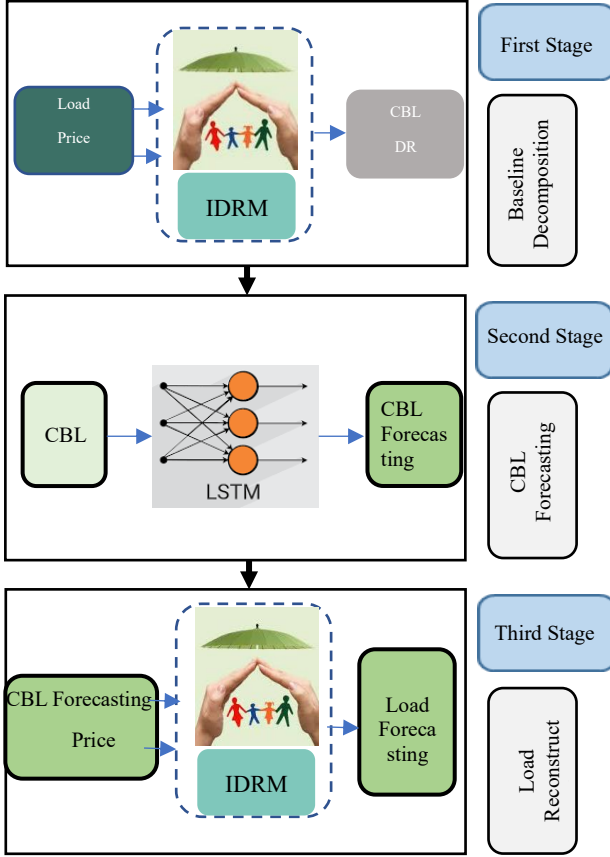


Figure 3. Flowchart of the proposed method.

A. Data Preprocessing and Baseline Decomposition

This subsection details the procedure used to extract the demand response (DR) component from the observed load data. The extraction process relies on the Index-based Demand Response Model (IDRM) introduced in Section II. Using the flexibility metric defined in Equation (5), the model produces an hourly estimate of DR, isolating the portion of the load attributable to incentive-driven behavioral adjustments. This explicit identification of DR effects yields a load profile without the influence of DR-related behavioral effects, which serves as a crucial foundation for accurate baseline prediction and the

subsequent stages of the forecasting framework. Once the DR component is computed, the baseline load is obtained through a direct subtractive decomposition:

$$B_t = L_t - DR_t \quad (7)$$

It should be noted that the proposed decomposition does not assume complete independence between the baseline load and the DR component. In this study, the baseline load is defined as the reference consumption pattern in the absence of temperature-sensitive cooling demand. Accordingly, changes in consumption associated with DR actions are considered deviations from this reference pattern and are represented by the DR component. This definition is used to distinguish the reference consumption pattern from DR-related variations in the observed load. When DR actions involve load shifting, identifying such load-shifting behavior solely from aggregate electricity consumption measurements is not possible, as the underlying behavioral causes of changes in consumption are not directly observable. Nevertheless, temporal consumption patterns and recurring consumption habits are partially captured through the historical input window used for training the LSTM model, allowing the forecasting process to account for temporal characteristics present in the observed load.

The resulting baseline load represents the reference, non-cooling component of electricity demand and provides a more consistent target for the forecasting model by separating the explicitly estimated DR-related variations from the observed load. The resulting baseline load profile is therefore used as the forecasting target for the LSTM model described in the next subsection.

B. LSTM-Based Baseline Forecasting

With the baseline series B_t extracted, the forecasting task focuses on predicting its future trajectory. A Long Short-Term Memory (LSTM) network is employed due to its strong capability to capture nonlinear dependencies and long-range temporal dynamics inherent in electricity consumption patterns. The model is supplied with the following inputs:

- historical values of the baseline load
- optional exogenous variables (e.g., ambient temperature, humidity, calendar features)

By training the LSTM on a behaviorally stable, DR-free target, the learning process becomes substantially more tractable. The baseline decomposition removes abrupt anomalies driven by DR events, ensuring that the model is exposed only to the intrinsic and structurally consistent components of load behavior. This leads to improved forecast accuracy and enhances the model's generalization capability across diverse operating conditions. The LSTM produces the predicted baseline load as:

$$\hat{B}_t = f_{LSTM}(B_{1:t}, X_{1:t}) \quad (8)$$

where X denotes the vector of exogenous input features. Model training is performed using a sequence-to-sequence architecture optimized with RMSE to maintain alignment with widely adopted accuracy metrics in industry-grade load forecasting.

C. Load Reconstruction with the DR Component

In the final stage, the predicted baseline is recombined with the DR component derived earlier. Because DR represents a behavioral response that can be quantified independently via IDRM, reintegrating it ensures that the final forecast captures both intrinsic and flexible components of demand. This modular reconstruction process has two main benefits:

1. It leverages the high accuracy of LSTM in modeling stable intrinsic consumption.
2. It preserves interpretability by explicitly incorporating DR via the index based IDRM model.

The result is a forecasting framework that combines the predictive capability of deep learning with the behavioral transparency required in modern smart grid applications.

IV. Numerical Studies

To evaluate the forecasting performance of the proposed framework, a comprehensive dataset consisting of one year of hourly electricity consumption and electricity price data was employed. The load and price data used in this study are both available at an hourly resolution. The electricity price data were obtained from ComEd's Hourly Pricing program and correspond to the real-time hourly electricity prices in the ComEd Zone of the PJM market. Each hourly price observation corresponds to the load observation for the same hour.

The dataset represents typical regional power system load profiles and provides a realistic basis for assessing the proposed forecasting methodology under practical smart grid operating conditions.

The forecasting task is formulated as day-ahead short-term load forecasting. A sliding input window of the previous 240 hours (10 days) is used to predict the subsequent 24-hour load profile. This window enables the forecasting models to capture both daily and weekly temporal dependencies. After generating the forecasting samples, the available data were divided chronologically into training and testing subsets using an 80%–20% split. Consequently, 6,816 hourly observations were used for training, while the remaining 1,704 hourly observations were reserved for testing. This chronological partition preserves the temporal ordering of the data, providing a realistic evaluation of day-ahead forecasting performance.

To comprehensively evaluate the proposed framework, its forecasting performance was compared with eight forecasting models representing different prediction paradigms, including ARIMA, ARIMA-IDRM, standard

LSTM, the proposed LSTM-IDRM, CNN, CNN-IDRM, AT-LSTM, and AT-LSTM-IDRM. These benchmark models were selected to represent widely adopted statistical, recurrent, convolutional, and attention-based forecasting approaches. Model performance was evaluated using Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Normalized Root Mean Square Error (NRMSE), where lower values indicate better forecasting accuracy.

Table 1. Performance Comparison of Forecasting Models with and without IDRM

	RMSE	MAPE	NRMSE
ARIMA	0.5271	11.12%	0.1315
ARIMA-IDRM	0.47	9.3%	0.1147
LSTM	0.395	6.63%	0.1128
LSTM-IDRM	0.322	5.38%	0.0804
CNN	0.439	8.24%	0.1271
CNN IDRM	0.361	6.05%	0.1044
AT LSTM	1.1051	16.04%	0.1579
AT LSTM IDRM	1.0969	14.87%	0.1567

Table 1 shows that the proposed LSTM-IDRM framework achieves the best overall forecasting performance among all benchmark models. Compared with the standard LSTM, the proposed framework reduces the RMSE from 0.395 to 0.322 (18.5%), the MAPE from 6.63% to 5.38% (18.9%), and the NRMSE from 0.1128 to 0.0804 (28.7%). These improvements demonstrate that the proposed framework significantly enhances forecasting accuracy while preserving the underlying LSTM architecture.

The proposed framework also consistently improves the performance of the other benchmark models. For the statistical forecasting model, ARIMA-IDRM reduces the RMSE by approximately 10.8% and the MAPE by 16.37% compared with the conventional ARIMA model. Similarly, CNN-IDRM achieves RMSE and MAPE reductions of approximately 17.8% and 26.6%, respectively, compared with the original CNN model. Although the AT-LSTM exhibits relatively smaller improvements, AT-LSTM-IDRM still produces lower forecasting errors than the corresponding AT-LSTM model across all evaluation metrics. These results indicate that the proposed framework consistently improves prediction accuracy regardless of the underlying forecasting architecture.

Figure4 presents representative forecasting results obtained using ARIMA, the standard LSTM, and the proposed LSTM-IDRM framework. As can be observed, ARIMA is unable to accurately track rapid load variations and peak demand periods, resulting in noticeable deviations from the actual load profile. The standard LSTM substantially improves prediction accuracy by learning nonlinear temporal dependencies; however, forecasting errors remain visible during periods of load fluctuations. In contrast, the proposed LSTM-IDRM closely follows the actual load profile throughout the forecasting horizon,

particularly during peak and transition periods, producing smoother and more accurate predictions.

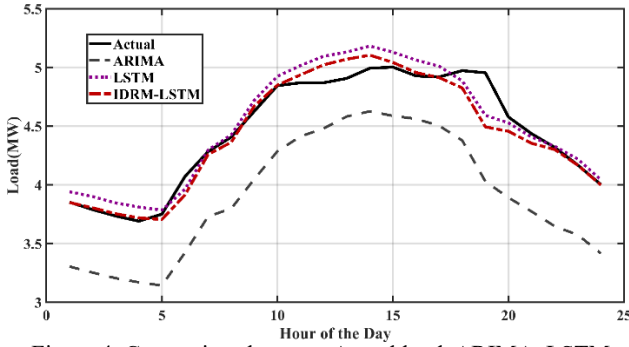


Figure 4. Comparison between Actual load, ARIMA, LSTM, and IDRM-LSTM predictions for the best-performing day.

The comparative results reveal a consistent trend across all benchmark models. Incorporating the proposed framework improves the forecasting performance of statistical, recurrent, convolutional, and AT-LSTM without requiring any modification to their internal network structures. This consistent behavior indicates that the proposed framework is not tied to a specific forecasting algorithm but can be effectively combined with diverse prediction models.

It is worth emphasizing that the objective of this study is not to develop another forecasting algorithm, but rather to introduce a general demand response decomposition framework that enhances the forecasting capability of existing prediction models. The consistent improvements achieved for ARIMA, LSTM, CNN, and AT-LSTM demonstrate that the proposed IDRM framework is independent of the underlying forecasting architecture and can be integrated with a wide range of forecasting models to improve short-term load forecasting accuracy.

Overall, the proposed IDRM-LSTM achieves the lowest forecasting errors among all evaluated models, with RMSE, MAPE, and NRMSE values of 0.322, 5.38%, and 0.0804, respectively. These findings demonstrate that the proposed framework provides a robust and practical solution for improving short-term load forecasting and offers a flexible preprocessing strategy for future smart grid forecasting and energy management applications.

To objectively evaluate the differences in forecasting performance, the Diebold–Mariano (DM) test was applied to pairwise comparisons of the prediction errors. The test was conducted using prediction errors obtained from the same forecasting horizon and the same test dataset for each pair of compared models. The results consistently indicate highly significant statistical differences across all three evaluations. When comparing ARIMA with LSTM, the DM statistic is 32.4846 (p -value < 0.001), indicating a statistically significant difference in predictive accuracy between the two models. The comparison between ARIMA and the proposed

IDRM–LSTM model yields a DM statistic of 36.5976 (p -value < 0.001), also indicating a statistically significant difference in predictive accuracy. The direct comparison between LSTM and IDRM–LSTM also yields a DM statistic of 11.0690 (p -value < 0.001), indicating that the difference in forecasting performance between the two models is statistically significant. Together with the forecasting error metrics, these results confirm that the proposed IDRM–LSTM model provides superior forecasting performance and that its improvement over the conventional LSTM is statistically significant rather than attributable to random variability.

To further assess the robustness of the proposed IDRM-based forecasting framework, a sensitivity analysis was conducted by varying three key parameters of the IDRM: the duration of high-load consumption D , the nonlinear transformation of the winter-to-summer power consumption ratio μ_t , and the financial incentive factor ρ . For each sensitivity analysis, the remaining model settings were kept unchanged, and the forecasting performance was evaluated using RMSE, MAPE, and NRMSE. The results are presented in Table 2.

Table 2. Sensitivity Analysis of LSTM-IDRM

Parameter	RMSE	MAPE	NRMSE
$D=3$	0.375	6.83%	0.0936
$D=5$	0.383	6.57%	0.0956
$D=7$	0.362	6.52%	0.0902
$D=9$	0.368	6.4%	0.0919
μ_t	0.483	7.14%	0.1205
μ_t^2	0.322	5.38%	0.0804
μ_t^3	0.37	6.91%	0.0984
$\rho = 0.9$	0.355	5.76%	0.0835
$\rho = 1$	0.322	5.38%	0.0804
$\rho = 1.1$	0.37	6.2%	0.0924

First, the sensitivity of the LSTM-IDRM framework to the duration parameter D was examined by considering values of 3, 5, 7, 9, and 11. The results show that the forecasting performance remains relatively stable for $D=3$ to $D=9$, whereas a noticeable degradation is observed at $D=11$. Among the tested values, $D=7$ provides the lowest RMSE and NRMSE, with values of 0.362 and 0.0902, respectively. The lowest MAPE is obtained for $D=9$, with a value of 6.40%. In contrast, increasing D to 11 increases the RMSE, MAPE, and NRMSE to 0.423, 7.14%, and 0.1054, respectively. These results indicate that the proposed framework is relatively robust to moderate variations in the high-load duration parameter. However, an excessively large value of D may lead to a less representative characterization of the high-load consumption period and consequently reduce forecasting accuracy. Second, the sensitivity of the proposed framework to the nonlinear transformation of the winter-to-summer power consumption ratio was investigated by comparing first-, second-, and third-order formulations of

μ_t . The results show a clear advantage of the quadratic formulation. The use of the first-order formulation results in an RMSE of 0.483, an MAPE of 7.49%, and an NRMSE of 0.1205. In contrast, the quadratic formulation substantially reduces these errors to 0.322, 5.38%, and 0.0804, respectively. The third-order formulation also improves upon the first-order formulation, but its performance remains inferior to that of the quadratic formulation, with an RMSE of 0.370, an MAPE of 6.91%, and an NRMSE of 0.0984. Therefore, among the tested formulations, the quadratic transformation of the winter-to-summer power consumption ratio provides the most favorable representation for capturing the nonlinear effect of consumption behavior. Finally, the sensitivity of the forecasting performance to the financial incentive factor ρ was evaluated using values of 0.9, 1.0, and 1.1. The results indicate that $\rho=1.0$ provides the best overall forecasting performance, achieving an RMSE of 0.322, an MAPE of 5.38%, and an NRMSE of 0.0804. Reducing the incentive factor to 0.9 increases the RMSE and NRMSE to 0.355 and 0.0835, respectively, while increasing it to 1.1 results in higher errors of 0.370 and 0.0924. The corresponding MAPE values are 5.76% and 6.20%, respectively. These results indicate that the relationship between the financial incentive factor and forecasting accuracy is not necessarily monotonic. Instead, changes in the incentive factor affect the estimated DR component and consequently influence the accuracy of the reconstructed load profile.

Overall, the sensitivity analysis demonstrates that the proposed IDRMLSTM framework maintains relatively stable forecasting performance under moderate variations in the key IDRML parameters. The results further show that the quadratic transformation of μ_t provides the best performance among the tested alternatives, while $D=7$ and $\rho=1.0$ provide the lowest RMSE and NRMSE among their respective tested values. These findings provide additional evidence that the forecasting improvements obtained by the proposed framework are not solely associated with a single arbitrary parameter setting.

V. Conclusions

This work presents a structured and interpretable forecasting framework that integrates an index-based Demand Response model (IDRM) with an LSTM neural network to explicitly account for DR-driven behavioral variability in load profiles. By quantifying DR through three operational indicators and isolating its effect from the observed consumption, the proposed methodology reconstructs a stable baseline load that better reflects the intrinsic physical demand. This decomposition effectively mitigates short-term behavioral noise, enabling the LSTM to learn prevailing temporal patterns with greater fidelity. Comprehensive numerical experiments using a full year of

real-world data demonstrate the superiority of the proposed framework over both traditional linear models and standard deep learning approaches. The IDRMLSTM achieves consistent improvements across all error metrics and reduces RMSE by approximately 18.5% compared with the baseline LSTM. Furthermore, the Diebold–Mariano statistical analysis confirms the significance and robustness of these enhancements, with all pairwise comparisons yielding large DM statistics and near-zero p-values. These results establish that the gains obtained through IDRML are systematic and originate from improved modeling of DR-induced structural variability rather than random fluctuations.

Overall, the findings underscore the importance of explicitly incorporating Demand Response effects into modern load forecasting methodologies. By offering an interpretable and operational representation of DR, the proposed framework enhances predictive accuracy, robustness, and practical usability—particularly in power systems with growing flexibility and consumer participation. The demonstrated performance indicates that the IDRMLSTM approach can serve as a reliable tool for short-term operational planning, contributing to more informed decision-making in emerging smart grid environments.

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