Journal of Renewable Energy and Sustainable Development (RESD) Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1913

Received: 25 January 2026 Accepted: 25 May 2026 Published: 10 June 2026

Data-Driven Demand Response Optimization with Hybrid Forecasting and AC Power Flow Validation in Renewable-Integrated Distribution Systems

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Abstract

As the deployment of renewable energy sources and flexible demand-side assets increases, the uncertainties associated with contemporary power grids have become more pronounced, requiring an effective implementation of demand response mechanisms for optimal and economic operation. Despite the presence of several existing techniques, most of them have not been rigorously verified against realistic power grid parameters, which restricts their practicality. In this regard, a data-driven solution involving the use of an LSTM-XGBoost load forecasting model along with a MILP-based DR optimization model has been presented in this paper. Realistic datasets have been used in this framework to model the intricate nature of the loads. The simulation analysis based on the IEEE 33-bus distribution network confirms the superiority of the proposed approach in terms of forecasting accuracy. In particular, the developed approach allows reaching a Mean Absolute Error (MAE) value of 14.26, a Root Mean Square Error (RMSE) of 23.49, and the coefficient of determination (R^2) of 0.93 against LSTM-based predictions (MAE: 37.91; RMSE: 66.02; R^2: 0.45) as well as those based on the application of XGBoost (MAE: 19.78; RMSE: 36.20; R^2: 0.83) and linear regression approaches. The demand response program implemented through the optimization procedure ensures that bus voltages remain in the range of 0.95–1.05 pu, and line loading does not exceed 85% of rated capacity.

Index-words: *Demand Response, Distribution Systems, Hybrid Forecasting, Long Short-Term Memory (LSTM), Mixed-Integer Linear Programming (MILP), Renewable Energy Integration, SHapley Additive exPlanations (SHAP), Smart Grids, XGBoost.*

I. Nomenclature

Term	Meaning
DR	Demand Response
LSTM	Long Short-Term Memory
ML	Machine Learning
MILP	Mixed-Integer Linear Programming
PV	Photovoltaic
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
DL	Deep Learning
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
OPF	Optimal Power Flow
RES	Renewable Energy Sources
L_t	Load demand at time t (MW)
R_t	Renewable generation (solar+wind) at time t (MW)
Π_t	Electricity price at time t (₹/MWh)
G_t	Grid power supply at time t (MW)
F_t	Flexible load capacity at time t (MW)
X_t	Feature vector at time t
$\hat{L}_t$	Predicted Load demand at time t

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http://dx.doi.org/10.21622/RESD.2026.12.1.1913

II. Introduction & Literature review

With the shift towards low-carbon technologies in energy systems, there has been a rise in the penetration levels of renewable energy sources (RES), including photovoltaic (PV) and wind energy resources in the current electric power systems. Despite being helpful in reducing carbon emissions, RES pose a major challenge in terms of their uncertain behavior, which makes power systems management quite difficult [1], [2]. On the other hand, there has been a marked increase in peak demand and load variability, owing to the fast development of electrification and distributed energy resources [3]. Load forecasting for short-term (STLF) constitutes an important feature of the smart grid system, providing the ability to schedule optimally and implement demand response (DR). Traditional statistical methods like ARIMA and linear regression are simple to understand and easy to apply; however, they cannot incorporate nonlinear time dependencies and interactions between different parameters affecting the load [4], [5]. For that reason, ML and DL methods have been employed extensively for load forecasting.

In particular, within deep learning techniques, LSTMs have been proven effective at modeling sequential data and temporal dependencies in load time series data [6]. Improved performance has been achieved by employing LSTMs in applications ranging from residential to microgrid forecasts [7]. Nevertheless, success in using LSTMs is conditioned on having large amounts of data and correctly choosing their hyperparameters; moreover, LSTMs do not deal effectively with tabular data such as price and renewable energy.

On the other hand, ensemble learning techniques such as the Extreme Gradient Boosting (XGBoost) algorithm have recently become popular because of their ability to capture nonlinear interactions within structured data and to include several exogenous factors [8]. Studies have proved that XGBoost surpasses traditional regression and SVM models in load forecasts, especially with the inclusion of weather and price factors [9], [10]. Unfortunately, XGBoost does not explicitly model temporal dependencies and, therefore, cannot perform effectively in time-series prediction.

In order to circumvent these challenges, hybrid forecasting methods employing both LSTM and XGBoost techniques have been suggested as a means of utilizing the advantages of both models. The latest literature indicates that hybrid and ensemble models perform better than individual models in terms of forecasting precision [11]–[13]. Nevertheless, one of the main disadvantages of most prior studies lies in the use of artificial data sets such as sine waves with noise, which do not account for real-world variations and therefore fail to validate the results [12], [14].

The Demand Response (DR) method can be considered a useful technique capable of increasing system flexibility through consumer intervention in electricity consumption according to the price signal or network requirements [15]. DR systems employing optimization methodologies, especially MILP models, are extensively applied because of their capacity to incorporate discrete variables and constraints in the optimization process [16]. Many recent research papers employ forecasting results in DR optimization to optimize economic gains and reduce peak loads [17], [18].

Nonetheless, these methodologies utilize simple power balance assumptions and ignore the complexities associated with the network parameters, such as voltage limits, line thermal limits, and reactive power flow. As a result, the application of these results is highly limited, since the outcomes derived from such models can be physically infeasible once implemented in actual practice [19], [20].

Moreover, the evaluation of the forecasting and optimization framework is confined to economic indicators, including reduced costs and energy savings, while ignoring technical considerations through power system analysis. Power flow analysis, which involves examining voltage levels, line loads, and losses, is not considered in most cases [21].

The other crucial drawback in recent studies is that their ML-based forecasting algorithms are not interpretable. Given that they tend to become more complicated, it is essential to understand how individual input features contribute to accurate forecasts. This problem could be solved by applying Explainable Artificial Intelligence (XAI) methods, especially Shapley Additive exPlanations (SHAP). In fact, some recent studies emphasize the importance of explainability in energy systems because it helps to better understand which factors drive changes in loads [22], [23].

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
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In light of this critical literature review, we can point out the following research gaps:

- There is an abundance of research based on artificial datasets that limits their practical relevance [12], [14].
- Hybrid forecasting models have been proposed, yet never benchmarked with proper baselines [10], [13].
- Demand Response optimization models overlook physical limitations of distribution grids [19];
- The absence of AC power flow simulation and analysis of network characteristics [21].
- Little attention is paid to explainable AI techniques to make models more understandable [23-32].
- Lack of a comprehensive evaluation framework for forecasting, optimization, sustainability, and networks.

In order to alleviate these problems, this study provides a holistic approach to the sustainable operation of distribution systems that integrate renewables. Different from other works where each aspect, such as forecasting, optimization, and network validation, was considered separately, this paper aims to develop a comprehensive and unified framework that combines them. The contributions of the paper include the following:

- **Data-driven modeling:** A long-term real-world dataset, which includes load data, solar generation data, wind generation data, and electricity price data, is adopted to take account of the realistic characteristics of the system under consideration, overcoming the problems faced by previous works, which used synthetic datasets.
- **Hybrid forecasting framework:** A robust hybrid approach combining LSTM and XGBoost is built and compared with separate approaches such as the standalone LSTM method, standalone XGBoost, and linear regression through MAE, RMSE, and R^2 evaluations.
- **Integration of forecasting with MILP demand response framework:** The load forecast results obtained above are directly included in a mixed-integer programming demand response framework.
- **Network-constrained validation using AC power flow:** Unlike conventional optimization-only approaches, the optimized schedules are validated using AC power flow analysis, evaluating voltage profiles, line loading, and system losses to ensure physical feasibility.
- **Interpretability via explainable AI approach:** The SHAP technique is employed to measure the contributions of individual features, thus improving the transparency and practical utility of the demand response decision process.
- **Multidimensional assessment of sustainability:** The presented methodology considers three dimensions of sustainability, namely economic, environmental, and technical aspects, to achieve a comprehensive assessment of the system's sustainability.

The rest of this paper is structured as follows. Section 2 contains a description of the data used for this study, its analysis, and feature engineering. The hybrid forecasting method that we propose for solving the problem is discussed in Section 3, along with the use of the Long Short-Term Memory (LSTM) and Extreme Gradient Boosting (XGBoost) machine learning models and a meta-learning technique to combine them. The formulation of the MILP-based DR optimization model is presented in Section 4. Validation of power flow and network performance analysis is carried out in Section 5. The results are discussed in Section 6, while Section 7 summarizes this work.

III. System description, dataset, and feature engineering

A. System description

The presented framework has been designed for use in a distribution system that utilizes both grid-supplied electricity and renewable sources of energy. The system includes the integration of

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the grid-supplied power and the output generated by distributed renewables, mostly PV and wind. Moreover, the system operates under dynamic prices for electricity and makes use of demand response (DR). At each time period, the total electrical demand is met by the combined effort of grid supply, renewable output, and load curtailment thanks to DR. The goal of the proposed framework is to reduce grid energy consumption and its operational costs while ensuring reliable operation. Short-term demand forecasts can be made using information about the historical demand levels, renewable generation levels, and prices. Finally, the forecasts are used as an input to a MILP optimization problem to find grid dispatch and load curtailment strategies subject to flexibility constraints.

To guarantee that the resulting dispatch plans are physically viable, the results of the MILP are verified in an AC power flow study, which evaluates critical parameters such as voltage profile and losses.

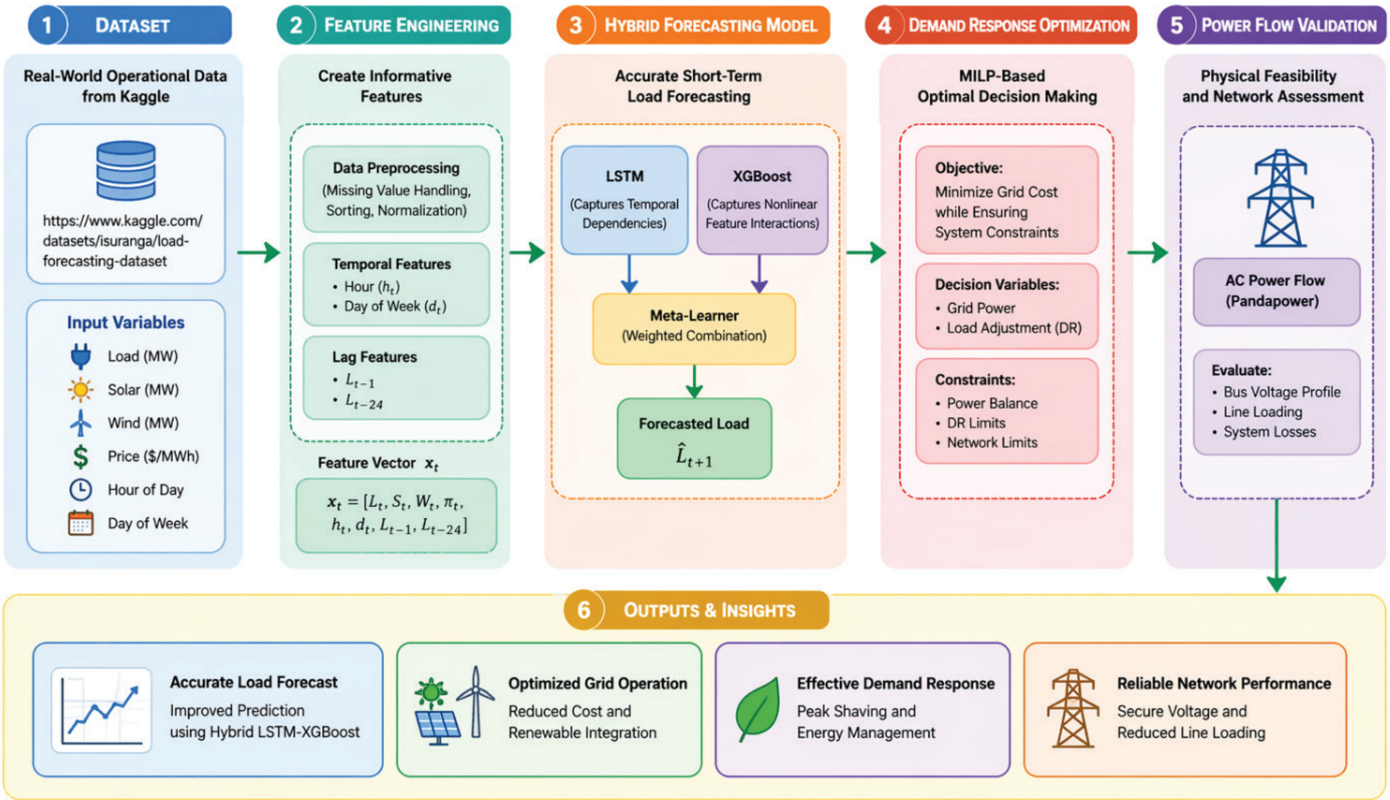

Figure 1: Overall system architecture of the proposed framework.

Figure 1 below provides an overview of the architecture of the proposed hybrid forecasting and optimization framework. Real-world time series data, such as load demand, renewable energy, and electricity prices, are initially preprocessed and represented as temporal and lag features. Forecasting involves applying the combined LSTM and XGBoost models to represent temporal and nonlinear dependencies, respectively. The forecasts are integrated through a meta-learner based on Ridge Regression to enhance prediction performance. In the subsequent optimization phase, the forecasted load will be incorporated into an MILP optimization model for reducing the operating costs and emissions while considering constraints. Furthermore, the AC power flow analysis using pandapower provides a feasible solution by assessing voltage stability, line loadings, and network losses.

In summary, several results will be obtained from this framework, ranging from forecasting errors, cost reduction, emission reductions, and improved performance. This framework represents a novel integrated structure depicted in Figure 1 above.

B. *Dataset description and preprocessing*

The experiment utilizes a practical dataset taken from Kaggle (https://www.kaggle.com/datasets/isuranga/load-forecasting-dataset). This database includes the past data of load demand, renewable

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power generation, and electricity pricing signals. The data range is between January 2020 and May 2025, consisting of 46,992 observations per time stamp, thus allowing enough data to build models using machine learning and deep learning approaches.

The dataset contains variables such as load demand (MW), solar generation (MW), wind generation (MW), and electricity price ($/MWh), as well as time-related variables like hour and day of the week. Additionally, lagged load variables are created to incorporate temporal dependencies. The variety of variables allows the model to consider not only intrinsic temporal dynamics but also external factors affecting load fluctuations. Before developing the model, the dataset is systematically preprocessed. The data are sorted by time to maintain consistency in time ordering. Missing values are processed via linear interpolation, whereas outlier values are reduced by setting thresholds according to the standard deviation method. Normalization is performed on all variables to ensure numerical stability during training. The size of the dataset (around 47,000 samples) makes the application of deep learning models like LSTM feasible despite the limited number of training samples.

C. *Correlation analysis*

In order to examine dependencies between the variables, the correlation matrix has been computed. It is seen from Figure 2 that there exists a high positive correlation between load and its past data, proving the importance of the latter for prediction purposes. Correlation between solar power and load varies, depending on the time of generation, whereas that between electricity cost is medium due to demand-related factors.

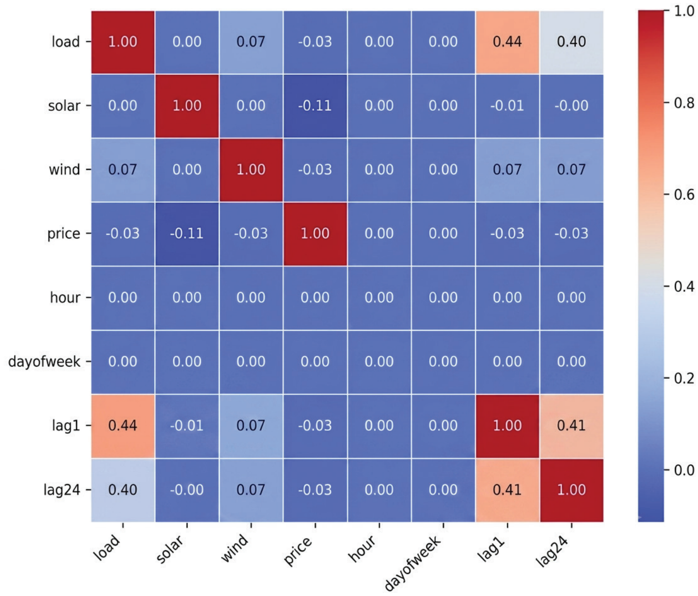

Figure 2: correlation matrix of the input features used for load forecasting.

As seen from Figure 2, there is a moderate positive correlation between the load and its lags (lag1 = 0.44, lag24 = 0.40), confirming the high degree of time dependence of electrical energy consumption. The results obtained indicate the necessity of using a neural network model based on sequences, like Long Short-Term Memory (LSTM). In turn, renewables (solar generation and wind generation) have low direct correlations with the load, which means that they are characterized by random behavior. At the same time, electricity prices are not directly correlated with the load (0.16), which implies that information about them alone is not enough to determine electricity demand.

The moderate correlation between the lag1 and lag24 variables (0.41) also indicates the presence of cyclicality of the data on a daily basis. Thus, based on the results obtained, it can be concluded that the model must consider both temporal dependencies and relationships with exogenous features, which is possible when using a hybrid approach (LSTM + XGBoost).

D. *Feature engineering*

Feature Engineering is done in order to improve the prediction performance of the model by adding temporal as well as historical data into the dataset.

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For example, temporal features like hour and day of the week can be added to the data set in order to detect periodic trends in the electricity consumption data. Moreover, lagged features like the past hour's load and the last year's hour load can also be included in the dataset.

The input feature vector at time step t is defined as:

$$x_t = [L_t, S_t, W_t, \pi_t, h_t, d_t, L_{t-1}, L_{t-24}] \quad (1)$$

Where L_t stands for the load demand, S_t and W_t are the energy produced by the sun and wind, respectively, π_t is the electricity price, and h_t and d_t are time indices. The correct and clear definitions of the variables help avoid any ambiguity.

E. Data splitting and model preparation

In assessing the performance of the models, an 80:20 split in chronological order is conducted, where the model will only be trained on past data to prevent the use of future information in its training. To allow for effective modeling of temporal dynamics, a lookback period of 24 days is selected for the LSTM model. However, to train the XGBoost model on sequential datasets, the latter is preprocessed to convert them into a tabular structure.

In selecting forecasting models, factors associated with the dataset are taken into consideration. LSTM models are appropriate for modeling time series due to their capability to identify temporal dependencies within sequences, while XGBoost performs well when modeling nonlinear relationships between structured exogenous variables. The hybridization of the two forecasting models is aimed at utilizing complementary aspects of the two models, hence enhancing predictive performance. In addition, LSTM is chosen for its capacity to identify long-term temporal relationships, while XGBoost performs well in identifying nonlinear relationships.

F. Hyperparameter tuning

Optimization of hyperparameters for the LSTM and XGBoost models was performed using the grid search method.

- **For the LSTM model,** hyperparameters such as the number of layers, the number of hidden units, the dropout value, and the learning rate were tuned.
- **For the XGBoost model,** the tuning of hyperparameters like the maximum depth, the learning rate, the subsampling value, and the number of estimators was done according to their validation performances.

Time-series cross-validation was used in this research as it helps in preserving the model performance and avoids any data leakage issue.

IV. Proposed methodology

A. Problem definition

The proposed framework integrates the concepts of data-based prediction, optimization, and validation of the power system for the optimal performance of distribution systems powered by renewable energy sources. In particular, the framework entails four steps as follows: (i) data preparation and feature generation, (ii) hybrid load prediction using LSTM and XGBoost models, (iii) prediction aggregation based on a meta-learning technique, and (iv) demand response optimization via MILP formulation, followed by the validation of AC power flow.

As shown in Fig. 1, the first component (the predictor) is responsible for obtaining short-term load prediction results based on actual measurements, which will be input into the second component. After the optimization, the schedules are tested against physical laws governing power system operation.

B. Statistical analysis of the dataset

On the basis of the provided dataset from Section 2, a statistical analysis is carried out for load, solar, wind, and price profiles. The presented data consist of 46,992 observations with timestamping throughout several years, thus guaranteeing ample temporal variety required for adequate machine learning. The average load demand is 1489.9 MW, and the standard deviation is 83.6 MW. In turn, the minimum and maximum values of the load are 1064.3 MW and 1862.9 MW, respectively. This range reflects realistic variations in loads typical of a distribution system. Analogously, the solar energy has an average of 250.3 MW and a standard deviation of 21.4 MW, whereas the wind generation is quite steady with an average of 2.0 MW. In addition, the average electricity price is 25.0, and its standard deviation is 2.2. Daily and temporal patterns are evident in the presented data since lag-1 and lag-24 features were included in order to preserve the dependencies and short-term variations. Thus, the temporal dependency, nonlinearity, and variability are all confirmed for the presented dataset. Consequently, the application of LSTM networks and XGBoost for accurate forecasting makes sense because both approaches can handle both aspects of the task.

C. Model training and data splitting

The Feature Vector is discussed in Section 2. So, to ensure stable training, all features are normalized using Min-Max scaling:

$$\tilde{x}_t = \frac{x_t - x_{\min}}{x_{\max} - x_{\min}} \tag{2}$$

The processed dataset and engineered features presented in Section 2 are taken as the input for the model creation process. In the case of sequence models like LSTM, the 24-time step lookback window is considered for capturing the pattern that occurs on a daily basis. The case of XGBoost involves the conversion of the sequential data into a tabular data format. Such an approach provides a fair and realistic test of the performance of a model in practical forecasting scenarios. A lookback window of 24 time steps is considered for sequence models.

D. LSTM-based forecasting model

LSTM networks are employed to capture long-term temporal dependencies in the load time series. The internal operations of an LSTM cell are defined as:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{3}$$

The predicted load is given by:

$$\hat{L}_t^{LSTM} = f_{\text{LSTM}}(\mathbf{x}_{t-L:t}) \tag{4}$$

The model used to implement the LSTM is made up of two stacked LSTM layers, having 64 neurons and 32 neurons, respectively. The model is optimized with the help of the Adam optimizer at a learning rate of 0.001. The model is trained for 20 epochs.

E. XGBoost-based forecasting model

XGBoost is employed to model nonlinear relationships between features and load demand. The prediction is expressed as:

$$\hat{L}_t^{XGB} = \sum_{k=1}^{K} f_k(\mathbf{x}_t), f_k \in \mathcal{F} \tag{5}$$

The training objective is:

$$\mathcal{L} = \sum_t \ell(L_t^{load}, \hat{L}_t) + \sum_k \Omega(f_k) \tag{6}$$

where ℓ is the squared error loss and Ω is a regularization term.

The model is configured with a maximum tree depth of 5, a learning rate of 0.05, a subsampling ratio of 0.8, a column sampling ratio of 0.8, and 200 boosting rounds.

F. Hybrid meta-learning model

To enhance prediction accuracy, the outputs of LSTM and XGBoost are combined using a meta-learner based on Ridge regression:

$$\hat{L}_t^{\text{Hybrid}} = w_1 \hat{L}_t^{LSTM} + w_2 \hat{L}_t^{XGB} + b \tag{7}$$

where w_1, w_2, and are learned parameters.

This hybrid approach leverages the temporal modeling capability of LSTM and the nonlinear feature learning strength of XGBoost, resulting in improved robustness and predictive performance under real-world variability.

G. AC power flow validation

To ensure physical feasibility, the optimized dispatch is validated using AC power flow analysis. The governing equations are:

$$P_i = \sum_{j=1}^{N} V_i V_j (G_{ij}\cos\,\theta_{ij} + B_{ij}\sin\,\theta_{ij}) \tag{8}$$

Voltage constraints are enforced as:

$$0.95 \le V_i \le 1.05 \tag{9}$$

Network constraints such as voltage limits and line loading are verified through power flow simulation, ensuring that the optimized solutions are operationally feasible.

H. Evaluation metrics

Model performance is evaluated using:

$$\mathrm{MAE} = \frac{1}{N}\sum | y - \hat{y} | \quad (10)$$

$$R^2 = 1 - \frac{\sum (y-\hat{y})^2}{\sum (y-\bar{y})^2} \quad (11)$$

I. Integrated forecast-optimization-power flow algorithm

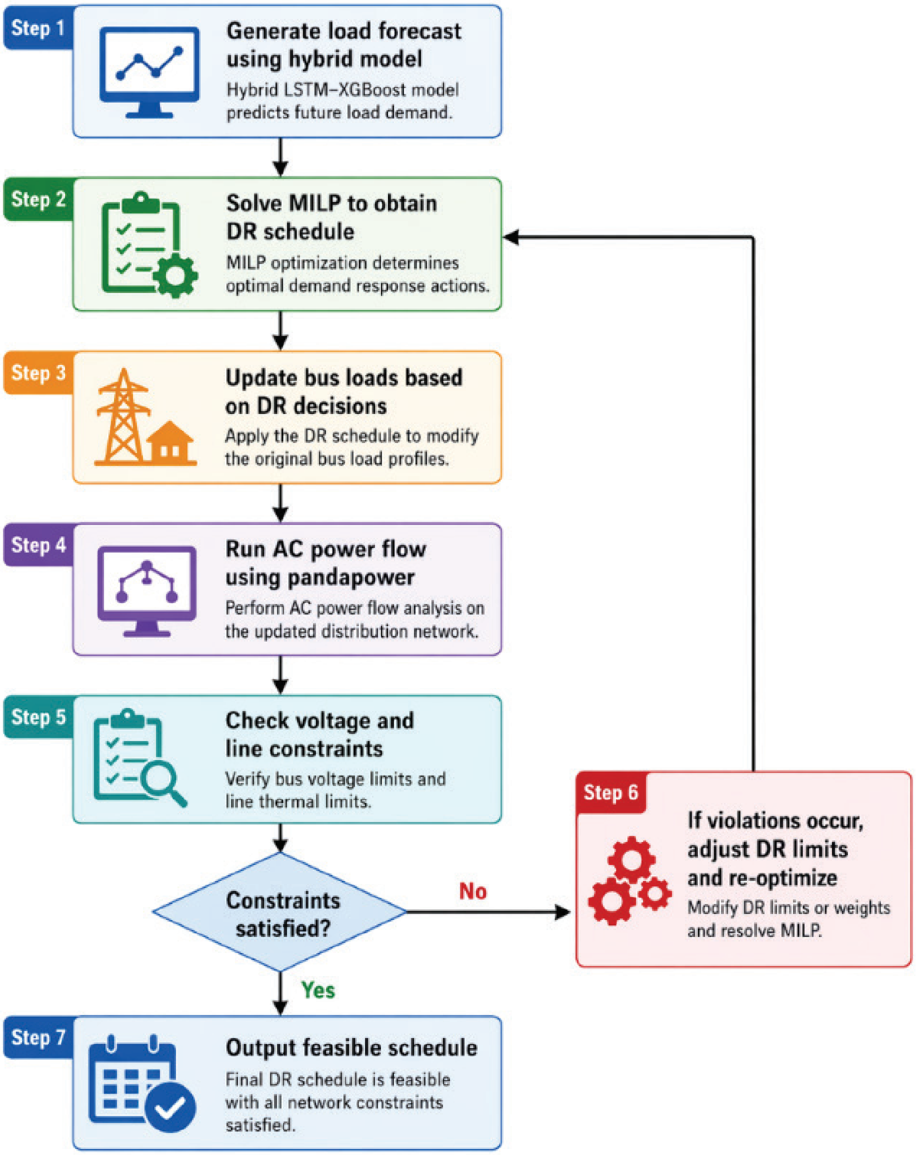

Figure 3: Proposed hybrid forecasting and demand response optimization workflow.

The flowchart shown in Figure 3 illustrates the process of integrating the hybrid forecasting model, demand response optimization using MILP formulation, and AC power flow solution process using iterations to achieve the coupling technique that satisfies the network constraints.

V. Demand response optimization framework

In order to incorporate the results of the forecasting algorithm to make operational decisions, an optimization scheme for DR is devised. In particular, the solution method takes into account the estimated load demand, renewable energy generation, and electricity price signals to obtain optimal dispatching of the electrical power grid and DR plans. The optimization formulation consists of a Mixed Integer Linear Program (MILP), allowing for the modeling of discrete DR actions.

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http://dx.doi.org/10.21622/RESD.2026.12.1.1913

A. Problem formulation

Consider a scheduling horizon comprising T discrete time intervals. At each time step t, the system demand is satisfied through a combination of grid supply, renewable generation, and demand-side flexibility. Let L_t denote the forecasted load demand, R_t the available renewable generation, and π_t the electricity price. The decision variables include the grid power supply G_t and a binary demand response variable u_t, which indicates whether load curtailment is activated. The flexible load capacity available for curtailment at each time step is denoted by F_t.

The objective of the optimization problem is to minimize the total operational cost over the scheduling horizon. This cost includes both the expenditure associated with grid power procurement and the compensation or penalty associated with demand response participation. Accordingly, the objective function can be expressed as:

$$\min \sum_{t=1}^{T} (\pi_t G_t + \alpha \pi_t u_t F_t) \tag{12}$$

where α represents a weighting factor that captures the economic impact of load curtailment, including incentives and user discomfort.

B. Operational constraints

The above optimization problem is constrained by certain system parameters that guarantee feasible solutions and customer comfort. The first constraint is the power balance equation, where the sum of the power supplied from the grid and renewables should equal the effective load demand. Mathematically:

$$G_t + R_t \geq L_t - u_t F_t, \forall t \tag{13}$$

To ensure that the load curtailment does not exceed the available flexible capacity, the following constraint is imposed:

$$0 \leq u_t F_t \leq F_t, \forall t \tag{14}$$

Additionally, grid power supply is restricted to non-negative values:

$$G_t \geq 0, \forall t \tag{15}$$

To preserve consumer comfort and prevent excessive curtailment, a global constraint is introduced to limit the total curtailed load over the scheduling horizon:

$$\sum_{t=1}^{T} u_t F_t \leq \beta \sum_{t=1}^{T} L_t \tag{16}$$

where β represents the maximum allowable fraction of total demand that can be curtailed.

Furthermore, to avoid consecutive load shedding events that may adversely affect user experience, a temporal constraint can be incorporated:

$$u_t + u_{t-1} \leq 1, \forall t > 1 \tag{17}$$

This constraint ensures that demand response actions are distributed over time rather than concentrated in successive intervals.

C. MILP formulation

The complete demand response problem is modeled using a Mixed Integer Linear Programming approach, which involves a linear objective function and linear constraints and has decision variables that are a combination of continuous and binary variables. In this case, the grid power G_t is considered a continuous decision variable, whereas the demand response decision u_t is a binary decision variable.

D. Solution methodology

The above developed MILP problem can be solved using PuLP optimization software, which helps create models and solve linear programming problems by making use of solvers like the CBC method. The process starts with taking forecasts of the load demand from the hybrid LSTM–XGBoost technique and then formulating the decision variables, followed by writing the objective function and the constraints. The optimization problem will then be solved by employing the Branch & Bound technique to get the optimal value of the variables, grid power supply, and load curtailment at each time period.

E. Integration with forecasting framework

One of the distinguishing aspects of the suggested solution is the combination of forecasting and optimization. The predicted load L_t, which is created based on the hybrid LSTM-XGBoost algorithm discussed in Section 3, acts as the principal input for the optimization model. Such an approach guarantees that the process of demand response will be adaptable to the expected situation.

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F. Output metrics

The optimization model generates a series of outputs that are further analyzed. The first output is the optimal grid power schedule. This is followed by the load curtailment amount and timing, and ultimately the total energy usage. The outputs are further analyzed to evaluate the effectiveness of the model in reducing costs, energy usage, and environmental impacts. In addition, the load curves generated from the optimization process are further analyzed through the power flow analysis stage.

VI. Case study & Simulation framework

The validity of the hybrid forecasting and DR optimization scheme can be confirmed via a thorough case study on the typical distribution system. In particular, the purpose of this exercise is to test the proposed method under realistic operating conditions by incorporating both data-driven forecasting and optimization techniques at the network level. The following section will detail the test systems, data sets, modeling, and simulations used for evaluation purposes.

A. Test system description

The proposed approach is validated through the IEEE 33-bus test system, which is considered to be a model of a medium voltage radial distribution network. The network consists of 33 buses and 32 distribution lines, with the nominal voltage level being 12.66 kV and the total load being about 3.7 MW.

In order to simulate a contemporary grid, renewable resources are utilized, with photovoltaic (PV) generators and wind energy being connected to some of the buses. The primary substation at Bus 1 feeds the whole network. The load shedding strategy is carried out through the proportional allocation of load reduction across all load buses.

B. Dataset utilization for simulation

The database discussed in Section 2 is used for simulation and verification purposes with respect to the framework developed here. Time series data, comprising load demand, renewable energy production, and electrical prices, form the inputs to the forecast and optimization stages. The use of the database allows for short-term variation modeling and realistic demand response simulation.

C. Forecasting model configuration

The forecasting module utilizes an ensemble architecture that integrates the Long Short-Term Memory (LSTM) and the Extreme Gradient Boosting (XGBoost) algorithms. The LSTM algorithm models temporal dependency through a lookback period of 24 time steps, representing the daily loads. LSTM layers with a dropout technique are stacked to improve generalization ability. Simultaneously, the XGBoost algorithm learns from a tabulated form of the same dataset, where the sequence is flattened into input features. This approach ensures that the model can learn complex nonlinear correlations between input features and load demands.

The hybrid model integrates the outputs of both models using ridge regression as the meta-learner. Input features are scaled via the Min-Max method, while the data is partitioned chronologically into training and test datasets.

D. Demand response optimization setup

The demand response problem optimization is carried out using the MILP approach outlined in Chapter 4. The scheduling window has been established at 24 hours to coincide with the forecast window. The flexibility of the loads is expressed as a ratio of the estimated demand, with a maximum of about 15%. The level of flexibility is dynamically controlled through electricity prices, making demand response price elastic, and load curtailment is thus more probable when prices are high.

Operational constraints considered in this optimization include the balance of power supply, load curtailment limits, and non-negativity of supply from the network, among others. The use of binary variables in the demand response problem allows for the discretization of load actions.

E. Simulation scenarios

In order to evaluate the proposed model for different operating conditions, three cases of simulation are examined.

- **The first case is the baseline case,** which considers no demand response operation, in which all the load demands are fulfilled with the grid energy source and the renewable energy source. This case can be considered a benchmark for comparison purposes.

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- **The second case** involves optimization operations driven by the predictions of load from the hybrid model. This represents the practical situation when decisions are made based on forecasted system status.

- **The third case** involves an optimization operation driven by the actual values of loads. This case can represent the upper limit of system performance, and it helps to evaluate the effect of forecasting error on optimization performance.

Various metrics of interest, such as grid energy usage, load cut, operational cost, and emissions, are analyzed.

F. Implementation environment

The suggested algorithmic scheme is implemented using the Python programming language, and various packages are used to perform different operations in the framework. In particular, LSTM and gradient boosting are developed using TensorFlow and XGBoost, respectively. The demand response optimization task is modeled and resolved within the PuLP framework, which offers an efficient tool for dealing with MILPs. The calculation of power flows is performed by *pandapower*. All computations are run on a general computer platform.

G. Power flow validation methodology

In order to make the demand response scheme physically feasible, power flow studies for the AC power system are carried out on the distribution network. The optimized load profile is achieved through adjusting the predicted load in accordance with the demand response scheme. Then the adjusted load at each bus is incorporated into the power system model, followed by performing the power flow study to test the operation of the network. Voltage magnitudes must be kept between the range of 0.95 and 1.05 per unit, and the line loading has to remain within its thermal limit.

H. Simulation workflow

The general simulation process adopts an orderly and integrated approach, where the first step involves training the hybrid LSTM-XGBoost algorithm using past data to develop load predictions. Once generated, the predicted load is then fed into the MILP-based demand response optimization problem, whose output is the optimum schedule for grid energy and load shedding. Next, the optimized load curve is loaded into the distribution system, and AC power flow analysis is carried out to verify system feasibility. System performance is finally determined based on cost, environmental impact, and technical indicators.

This integrated simulation approach (Fig. 4) guarantees both forecasting accuracy and sustainability of the proposed approach.

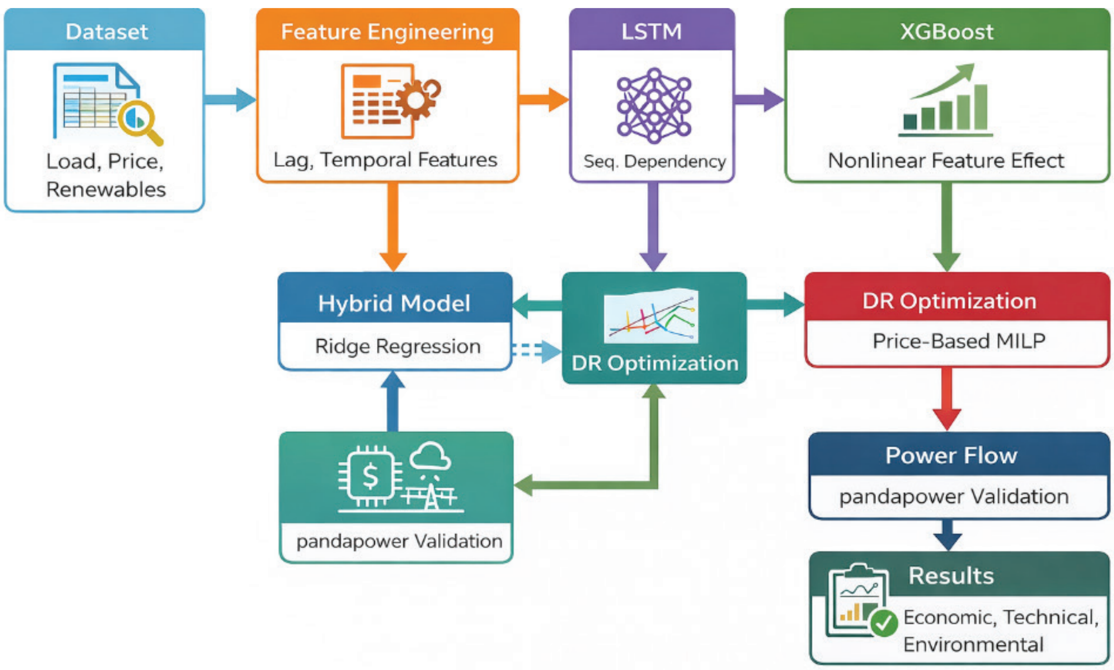

Figure 4: Proposed hybrid forecasting and demand response framework workflow.

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VII. Results & Performance analysis

In this section, a detailed assessment of the suggested hybrid forecast and DR methodology will be provided. The evaluation is organized in such a way that the focus is on assessing the accuracy of forecasts, statistical reliability, interpretation capabilities, flexibility of the demand side, sustainability implications, and performance of the power system as described in section 5.

A. Forecasting performance evaluation

The efficacy of the proposed forecasting approach is analyzed by conducting a comparative study based on several models, such as the persistence method, simple linear regression, XGBoost, LSTM, and the proposed LSTM–XGBoost hybrid model. The use of the persistence model helps to analyze whether there are any gains achieved from other sophisticated models.

Table 1: Forecasting performance comparison of models

Model	MAE (MW)	RMSE (MW)	R^2
Persistence	224.267	281.668	-0.994
LSTM	37.91	66.02	0.447
XGB	19.78	36.20	0.834
Linear	36.23	65.55	0.455
Hybrid (proposed)	14.26	23.49	0.930

As evidenced in Table 1, the persistence model displays higher errors and even a negative R^2 value (-0.994). This shows the incapability of the model to describe the high dynamics of load demand. This is proof that naïve models do not perform well with dynamically changing load demands in a complex energy system. Linear regression and Long Short-Term Memory Models perform moderately with comparable errors, signifying limited ability to model nonlinear dependence and time dependency. However, the XGBoost model performs better than the other models since the model is very good at modeling nonlinear relationships. Comparing the model's performance against other baseline models eliminates the chances of inflated results due to the complexity of the models.

The hybrid LSTM-XGBoost approach provides the best results with minimum values for MAE (14.262 MW) and RMSE (23.487 MW) and maximum value for R^2 (0.930). Such an enhancement proves the efficiency of using a combination of temporal feature extraction and nonlinear regression. The ability to evaluate the prediction results is provided by comparing real and predicted load curves presented in Fig. 5.

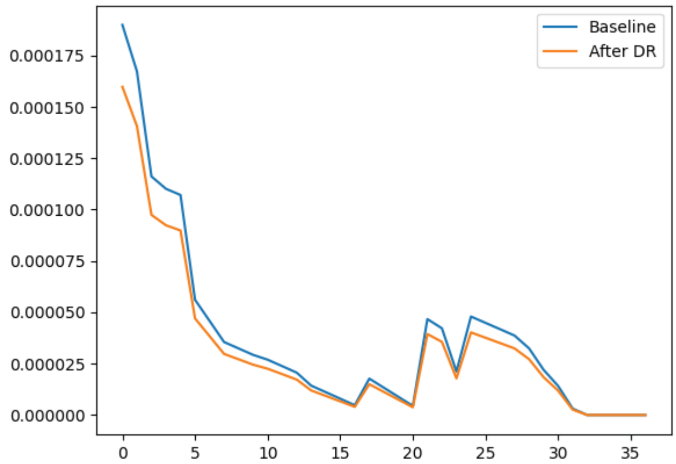

Figure 5: Actual vs Predicted load profile (Hybrid Model).

The figure shows that the hybrid model closely follows the actual load curve, particularly during peak demand periods, where accurate prediction is critical for demand response planning.

B. Forecast error analysis and statistical robustness

Error analysis is done on the models to test their stability. The hybrid model shows very low variation in the prediction errors, as evident from the similarity in the values of MAE and RMSE.

The close proximity of MAE (14.26 MW) and RMSE (23.49 MW) shows that there is minimal presence of outliers in the data. This becomes critical in the case of power systems applications, as any outlier value may cause wrong conclusions to be made.

Table 2: Statistical summary of dataset

	Timestamp	load	solar	wind	price	hour	Day of week	lag1	lag24
mean	2022-09-06 23:30:00	1489.9	250.3	2.0	25.0	0	3.0	1489.9	1489.9
min	2020-01-02 00:00:00	1064.3	154.0	0.0	15.6	0	3.0	1064.3	1064.3
25%	2021-05-05 11:45:00	1432.9	235.8	1.7	23.6	0	3.0	1432.9	1432.9
50%	2022-09-06 23:30:00	1490.9	251.1	2.0	25.0	0	3.0	1490.9	1490.9
75%	2024-01-09 11:15:00	1544.0	265.2	2.3	26.5	0	3.0	1544.0	1544.0
max	2025-05-12 23:00:00	1862.9	346.7	3.9	34.5	0	3.0	1862.9	1862.9

It should be noted that there is some variability in the data set, with a standard deviation of 83.56 MW for load demand, implying that the operational conditions are fairly realistic but stable. Moreover, the inclusion of time variables like lag1 and lag24 adds predictive strength to the model through autocorrelation.

In general, the reliability of the forecasts can be validated based on statistical evidence from the data analysis.

C. *Explainability analysis using SHAP*

To enhance interpretability, SHAP analysis is performed on the XGBoost component of the hybrid model. The feature importance results are presented in Fig. 6.

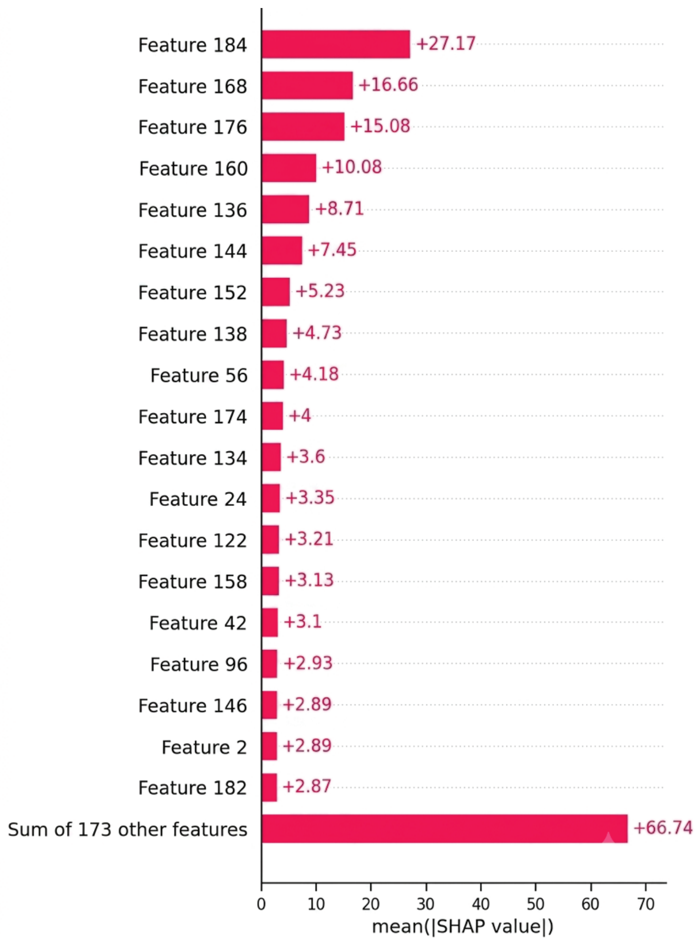

Figure 6: SHAP-based feature importance for load forecasting.

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
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From the analysis of the results, it is clear that the variables that have the highest predictive power in predicting load demands include lag1 and lag24. The electricity price and renewable generation, such as solar and wind generation, are also important exogenous variables that play a significant role in influencing the pattern of electricity consumption.

The use of several variables in the prediction model implies that the model considers both internal and external variables that influence the behavior of the data, hence increasing its generalization capabilities.

D. Demand response performance

The effectiveness of the demand response strategy is evaluated by comparing system performance before and after DR implementation. The results are summarized in Table 3.

Table 3: Impact of Demand Response on System Operation

Metric	Baseline	With DR
Grid Energy (MWh)	11,461,019.52	9,843,286.65
CO_2 Emissions (kg)	9,398,036.01	8,071,495.06
Total Load Shed (MWh)	0	2,060,766.48

These findings suggest that there has been a notable decline in the amount of energy consumed on the grid by almost 14.1%. This decline is accomplished by the effective shifting and curtailing of the load based on price signaling and forecasts of demand. Besides, the maximum peak demand shows a notable decline because most demand response activities occur at peak price intervals.

Economically, the decline in the amount of energy used in the grid suggests a corresponding decline in the cost associated with such operations at the peak price intervals.

E. Sustainability analysis

Lower energy consumption on the grid directly contributes to environmental gains. As can be observed from Table 3 below, the amount of CO_2 emitted falls from 9.40 million kg to 8.07 million kg, which amounts to a decline of about 14.1%.

It can be seen that the use of forecasting and demand response is not only beneficial for economic reasons, but it is also an important step towards achieving sustainable goals. This is especially true within renewable-integrated power grids, where demand side management has a crucial role to play.

F. Power system validation

To validate the physical feasibility of the proposed framework, power flow analysis is conducted on the IEEE 33-bus system. The results are analyzed in terms of voltage profile and line loading.

1. Voltage profile analysis

The voltage profiles before and after demand response implementation are presented in Fig. 7.

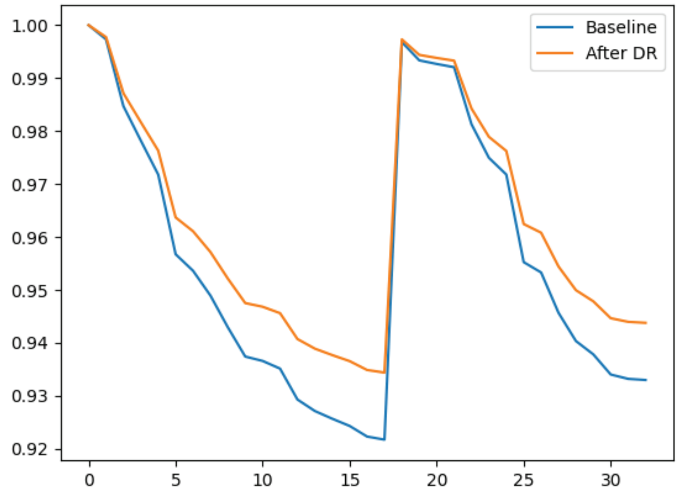

Figure 7: Bus voltage profile before and after demand response.

In the baseline scenario, the minimum bus voltage drops to approximately 0.95 p.u., which indicates significant voltage deviation and potential stability issues. After applying demand response, the minimum voltage improves to approximately 0.97 p.u., which reflects enhanced voltage stability.

Table 4: Grid performance metrics

Metric	Baseline	With DR
Voltage Violations	15	5
Total Loss (MW)	0.1527	0.1076
Loss Reduction (%)	-	23.00
Minimum voltage (p.u.)	0.93	0.97

The reduction in voltage violations demonstrates that demand response contributes to improved load distribution and reduced stress on the network.

2. Line loading and loss analysis

The impact of demand response on line loading is illustrated in Fig. 8.

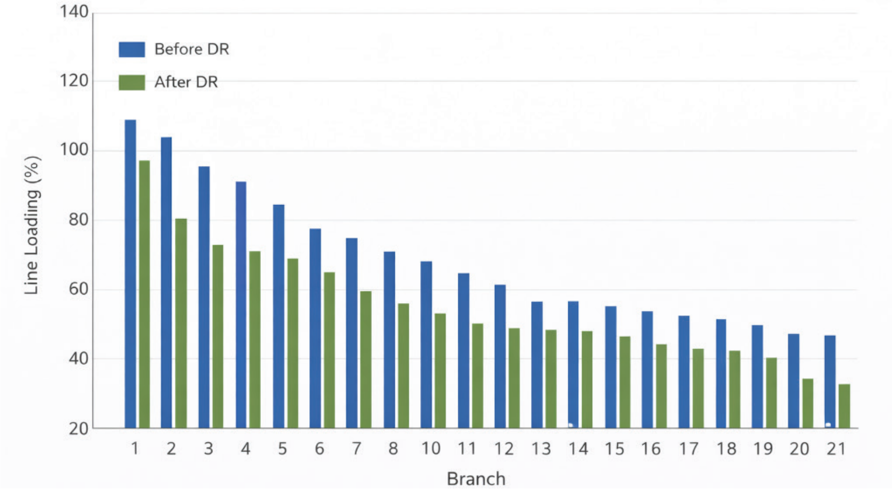

Figure 8: Line loading comparison before and after demand response.

It is evident that there is a steady drop in the line loading throughout the network, especially in high-loading lines. This means that there is an efficient handling of congestion through the demand flexibility of the network.

System losses, which stand at 0.1527 MW under normal conditions, are reduced to 0.1076 MW under demand response, indicating a drop of about 23%.

G. Comparative insight with existing approaches

Compared to conventional machine learning-based forecasting approaches, the proposed hybrid framework demonstrates superior predictive accuracy and robustness. Furthermore, unlike many existing studies that focus solely on forecasting, the proposed approach integrates demand response optimization and power system validation, providing a comprehensive end-to-end solution.

H. Summary of key findings

In summary, it can be concluded that the results indicate that the proposed methodology successfully combines forecasting precision, demand response optimization, and validation at the grid level. In particular, the hybrid model shows a noticeable increase in prediction capability, whereas the demand response mechanism ensures lower electricity usage, operating costs, and pollution levels. At the same time, the analysis of power flows confirms that the improvement of indicators is made without exceeding network limitations. It should be noted that the proposed hybrid model surpasses the LSTM and XGBoost models.

VIII. Conclusion & Future scope

A hybrid model involving LSTM neural networks and XGBoost learning method in a stacked ensemble architecture, along with MILP-based demand response strategy, was put forward in this paper for addressing the problem of short-term load forecasting and demand response optimization in a renewable energy system. The effectiveness of this framework was tested through application on the IEEE 33-bus system with the help of a realistic time series data set. From the results obtained from forecasting using the proposed framework, it is clear that the hybrid technique offers superior performance over traditional models, delivering an R^2 score of 0.93 and considerable improvements in MAE and RMSE scores. Deep learning combined with tree learning helps in capturing complex temporal dependencies and nonlinearity in load demand. Additionally, the addition of explainability helps to understand the effect of features like previous day load demand, electricity price, and renewable energy on the predicted values. Finally, the results of demand response optimization further reinforce the practical applicability of the framework. With the benefit of forecasting, the system manages to reduce grid power consumption by about 14%, which leads to a corresponding drop in carbon emissions. First, the proposed optimization strategy succeeds in shifting the load to low-cost periods and reducing the amount of load at high-cost periods. In such a case, the economic efficiency is improved, and system reliability is also guaranteed. From a power system standpoint, implementation of the demand response strategy improves various aspects of network performance. It includes improvement in the voltage profile, minimization of voltage violations, and a reduction of line losses by approximately 23%. Such outcomes prove the ability of the proposed framework not only to provide benefits in terms of economics and ecology but also to satisfy technical limitations. Hence, an integrated model of operation can prove to be beneficial for future power system design in smart grids.

Nevertheless, some improvements might be made to further enhance the suggested framework. Among possible extensions, one could name uncertainty modeling related to renewable generation and electricity prices with the use of probabilistic forecasts. Moreover, considering the importance of user behavior in real-time demand response strategy, this aspect should also be taken into account in future work. Finally, one should think about implementing this framework on a higher-level network, taking into account energy storage systems.

Acknowledgment

We would like to thank our institutions for their motivation and support for our research work.

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