ELECTRICITY DEMAND FORECASTING FOR POWER GENERATION ACROSS MULTIPLE REGIONS IN INDIA

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Abstract

Forecasting electricity demand is an important factor in maintaining grid stability, optimizing generation resources, and sustainable energy planning, especially in large-scale and heterogeneous power systems like India. This paper introduces a powerful, AI-based electricity demand forecasting system that incorporates multi-source data and state-of-the-art deep learning models to overcome the shortcomings of conventional statistical and standalone machine learning models. The suggested system uses real-time NASA POWER meteorological data and past demand data provided by Ember Energy and then undergoes extensive preprocessing, time synchronization, and feature engineering, such as lag variables, rolling statistics, and cyclical time encoding. A hybrid ensemble model of Neural Hierarchical Interpolation of Time Series (NHiTS) and iTransformer is created to be able to capture both time dynamics and multivariate dependencies. The NHiTS component is used to model multi-scale time dynamics (e.g., hourly, daily, and seasonal variations) and the iTransformer is used to model complex cross-variable relationships between weather parameters and electricity demand. A learnable fusion layer combines the outputs of both models to boost predictive accuracy. Experimental analysis shows that the proposed ensemble model has a Mean Absolute Percentage Error (MAPE) of 11.4% and an average forecasting error of 89.2% that is better than the single models and the traditional benchmarks. The coefficient of determination is also high (R 2>0.88) which means that the system has a high level of agreement between the predicted and actual demand. Moreover, the locality-aware scaling enhances the regional forecasting up to 12 times, which demonstrates the significance of spatial heterogeneity in demand modeling. Besides prediction, the system also has an intelligent energy recommendation module, which estimates the best distribution of energy mixes based on the predicted demand and weather conditions, with a recommendation accuracy of 92.5. The framework is implemented with the help of an interactive dashboard, which allows visualizing in real-time, multi-horizon forecasting (up to 30 days), and providing grid operators with decision support. On the whole, the suggested system proves to be very accurate, scalable, and practically applicable to the management of smart grids, which will lead to the increase in the efficiency of operations, decrease in the wastage of energy, and the further integration of renewable energy sources.

Keywords : Electricity Demand Forecasting, Time Series Forecasting, Deep Learning, NHiTS, iTransformer, Hybrid Ensemble Model, Smart Grid, Renewable Energy Integration, Energy Mix Optimization, Weather-Based Forecasting, Multivariate Time Series, India Power System

I. INTRODUCTION

Electricity demand forecasting is an important aspect of contemporary power system functioning, which allows planning the generation efficiently, maintaining the stability of the grid, and using the resources optimally. As the smart grids are becoming more complex and more sources of renewable energy are being incorporated, the demand prediction is becoming more difficult and necessary. The recent research highlights the significance of considering the spatial-temporal aspects and environmental parameters to enhance the accuracy of forecasts in smart energy systems [1].

Electricity demand prediction has traditionally been done using traditional statistical and time-series forecasting methods, yet these methods frequently do not capture complex nonlinear relationships and multi-scale temporal patterns found in real-world data. State-of-the-art deep learning models, including Neural Hierarchical Interpolation of Time Series (NHiTS), have shown a better ability to model hierarchical temporal relationships and long-term seasonal patterns [2]. Moreover, extensive literature points out that machine learning models are far more effective than classical methods in predicting peak demand due to their ability to deal with large-scale and high-dimensional data [3].

Regional variability, population density, and climatic diversity make electricity demand forecasting even more complicated in the case of large and diverse countries such as India. Empirical studies specifically designed to address the needs of Indian power systems have demonstrated that regional specifics and explanatory variables can significantly enhance the forecasting performance [4]. Moreover, the current machine learning systems offer powerful analytical tools to comprehend consumption patterns and improve predictive capabilities [5].

In addition to electricity demand, forecasting methods have also been used to other related areas like coal demand prediction where hybrid optimization methods have been effective in dealing with various factors affecting it [6]. Transformer-based architectures have become more recently a potent tool in time-series forecasting. The iTransformer model is an innovative model that uses variables as tokens, which allows the effective modeling of inter-variable dependencies and better prediction [7]. Other transformer-based implementations have shown good performance in predicting peak electricity demand in Indian power systems [8].

The introduction of machine learning into smart grid optimization has also contributed to the possibility of predicting energy consumption and contributing to sustainable energy management practices [9]. More complex models that integrate forecasting and scheduling systems have also been suggested to maximize the use of energy in renewable-based grids [10]. Furthermore, hybrid methods that integrate decomposition methods with attention mechanisms have demonstrated considerable enhancement in both short-term variations and long-term patterns in electricity loads data [11].

Recent research still confirms the usefulness of machine learning and deep learning method combination to enhance forecasting strength and precision [12]. Hybrid models, especially those that combine optimization algorithms with learning-based models, have proven to be very effective in long-term power system planning tasks [13]. Moreover, deep learning models that include weather variables have been shown to be very effective in reflecting the impact of environmental conditions on electricity demand, which also increases the predictability [14].

Although these improvements have been made, there are still difficulties in multi-scale time pattern and multivariate dependencies capture in a single framework. In order to overcome these shortcomings, this paper suggests a hybrid deep learning-based electricity demand forecasting model that combines NHiTS with iTransformer models. The suggested solution uses real-time weather forecasts and past demand data, along with sophisticated feature engineering methods, to provide precise and scalable predictions of multi-region power systems in India.

II. LITERATURE SURVEY

The prediction of electricity demand has been actively researched with a broad variety of statistical, machine learning, and deep learning methods, with recent studies aiming to enhance the accuracy of prediction by integrating spatio-temporal dynamics and external factors that impact demand, including weather conditions.

A spatio-temporal framework of predicting renewable energy production and demand in smart cities, suggested by Aljohani and Almansour [1], showed that the combination of spatial and meteorological characteristics of a city can greatly improve the forecasting results. Their work identifies the significance of integrating environmental and temporal data to make sound energy forecasts. Recent progress in deep learning has resulted in time-series forecasting architectures. The Neural Hierarchical Interpolation of Time Series (NHiTS) model proposed by Challu et al. [2] represents the multi-scale temporal patterns by hierarchical decomposition. The model has been successful in the modeling of long-term seasonality and complicated time reliance in energy demand data.

A thorough survey by Dai et al. [3] examined machine learning approaches to peak demand forecasting and concluded that deep learning models are more effective than the traditional statistical techniques in dealing with nonlinear relations and large data volumes. Their article highlights the increasing importance of artificial intelligence in contemporary power systems. With an emphasis on the Indian energy context, Hunt and Bloomfield [4] created data-driven electricity demand forecasting models across Indian states, emphasizing regional variability and localized modeling. Their results suggest that geographic and climatic diversity enhances the generalization of models and forecasting.

On the same note, Manohar et al. [5] have performed a comparative study on the use of advanced machine learning methods in energy demand prediction and have shown that hybrid and deep learning-based methods give better results than standalone models. Their work supports the necessity of the combination of various methodologies. Liu et al. [6] used hybrid optimization methods (GA–LSSVM) to predict coal demand under various conditions, which demonstrates the usefulness of using optimization algorithms with machine learning in solving complex energy forecasting tasks.

Transformer-based architectures have received considerable interest over the past few years. Liu et al. [7] proposed a new method, the iTransformer, which considers variables as tokens instead of time steps, allowing to model the inter-variable dependencies efficiently. This innovation enhances the knowledge of the relationship between weather variables and electricity demand. In line with this trend, Jha and Luhach [8] used transformer-based models to forecast Indian peak power demand, and they showed a higher accuracy and strength than the conventional neural networks. Their work confirms the relevance of attention mechanisms in actual power systems.

Maheshwari et al. [9] have also discussed the integration of machine learning in smart grid systems and emphasized the importance of predictive analytics to optimize energy consumption and improve sustainability. Their results highlight the significance of smart forecasting systems in the contemporary grid management. Moreover, Ibrahim et al. [10] suggested a combined forecasting and scheduling model of renewable-aided grids, which combines prediction models with energy management plans. Their methodology illustrates the way forecasting can have a direct impact on operational decision making.

Hybrid forecasting models have also been extensively studied. Oqaibi and Bedi [11] designed a hybrid model that integrates data decomposition methods with attention mechanisms, which have shown better results in electricity load prediction. They demonstrate in their work that a combination of several modeling strategies can be used to effectively describe both the short-term fluctuations and long-term trends.

Additionally, in support of this trend, Percuku et al. [12] revealed that a combination of machine learning and deep learning models improves forecasting accuracy and strength. Their work points to the advantages of mixed methods in the management of various and complex data. In the same way, Sun et al. [13] introduced a hybrid SSA-LSSVM model to predict long-term coal demand, which demonstrates the efficiency of combining optimization methods with machine learning to enhance the forecasting ability in energy systems. Lastly, Yang et al. [14] highlighted the significance of weather variables in deep learning models in electricity demand forecasting. Their analysis established that the environment including temperature and humidity are significant in determining the consumption patterns of electricity.

The recent developments in transformer-based architectures have had a profound effect on the time-series forecasting domain, especially in terms of long-sequence and multi-horizon prediction. The Informer model proposed by Zhou et al. [15] is a solution to the computational inefficiency of the traditional transformers, where the authors use a probabilistic sparse attention mechanism. This method is less complex in terms of time and is also very accurate in prediction, which makes it very appropriate in long sequence electricity demand forecasting scenarios. To achieve even greater interpretability and forecasting performance, Lim et al. [16] introduced the Temporal Fusion Transformer (TFT), a hybrid model, which combines attention mechanisms with recurrent layers to address the multi-horizon forecasting task. The model uses gating mechanisms and variable selection networks, which allow it to offer interpretable information on the importance of features and still have high predictive power.

Wen et al. conducted a thorough survey of the use of transformer models in time-series forecasting [17], noting that they are beneficial in capturing long-range dependencies and multivariate data. Other critical challenges that are also identified in the study are computational cost and data requirements and the increasing prevalence of transformer-based methods in forecasting tasks, including energy demand prediction. Before the use of transformers became commonplace, recurrent neural networks were instrumental in time-series modeling. Kong et al. [18] established the usefulness of Long Short-Term Memory (LSTM) networks in the short-term residential load forecasting. Their study demonstrated that LSTM models are able to effectively learn temporal dependencies and nonlinearities in electricity consumption, which formed the basis of future deep learning innovations in the field.

Summary of Literature Gap

Based on the above studies it is clear that:

• Deep learning models are more effective than traditional methods in learning nonlinear patterns.

Transformer-based and hybrid models are much more effective in improving the accuracy of forecasting.

Weather variables: Weather variables are essential in demand forecasting.

• Spatio-temporal and regional modeling improves performance.

III. PROPOSED METHODOLOGY

3.1. Introduction to the Proposed Framework

The proposed electricity demand forecasting system is a proposed end-to-end, data-driven architecture that combines real-time meteorological data, past energy demand data, and sophisticated deep learning algorithms to produce precise multi-horizon predictions and energy suggestions. The framework integrates the use of multi-source data collection, preprocessing, feature engineering, hybrid deep learning modelling, and generation of decision-support output in a single architecture. The system is particularly designed to multi-region forecasting within India, with the issues of nonlinear demand trends, weather sensitivity, and multi-scale time variations.

3.2. System Architecture

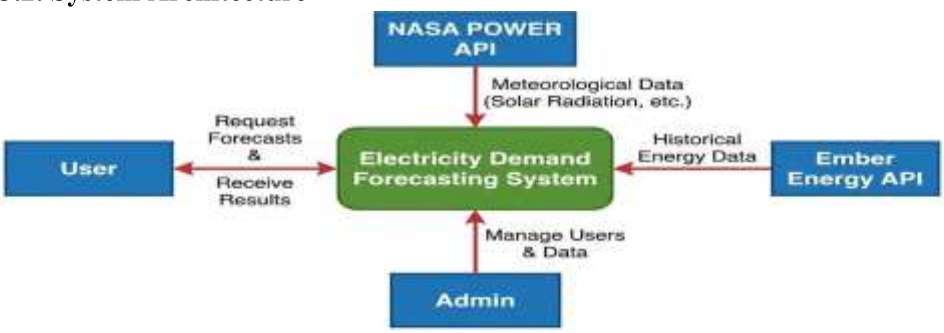

Figure 1: Context Diagram (Level 0 DFD) of the Electricity Demand Forecasting System

The high-level architecture of the electricity demand forecasting system is shown in Figure 1 in the form of a Level 0 Data Flow Diagram (DFD). The system is represented by a central processing unit that communicates with four main external entities:

• User: The user will enter input parameters, including location and forecast horizon and will get the outputs in the form of demand forecasts, visualizations, and energy recommendations.

• NASA POWER API: Provides actual and predicted weather information, such as temperature, solar radiation, humidity, and wind speed.
• Ember Energy API: Contains historical electricity demand and generation data to be used to train and validate models.
• Admin/Trainer: Maintains the system, retrains and data.

At this level, the system is considered to be a black-box model, which abstracts the internal processes like preprocessing, feature engineering, and model inference. The architecture emphasizes the smooth combination of external data sources and AI-based analytics, which is the basis of precise and scalable forecasting.

3.3. System Logical Workflow

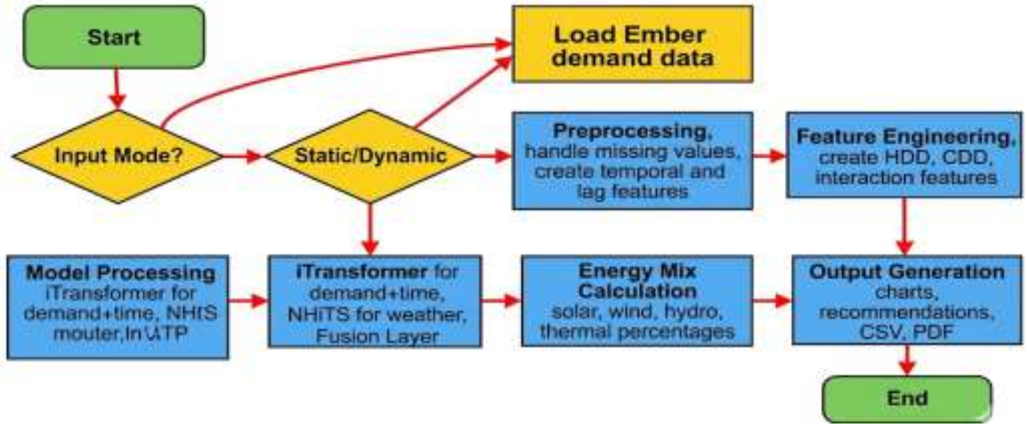

Figure 2: Electricity Demand Forecasting System Logical Workflow.

Figure 2 shows the workflow of the proposed system step by step, illustrating how the raw input data can be transformed into actionable insights.

Step 1: Enter Mode of input.

The system has two modes:

- Static Mode: Trains and evaluates using historical data.
- Dynamic Mode: Retrieves real-time weather conditions to do live forecasting.

Step 2: Data Acquisition

The data on electricity demand is obtained in the Ember Energy dataset, and the weather data is obtained in NASA POWER API. This makes sure that both exogenous and temporal variables are included.

Step 3: Data Preprocessing

Raw data undergoes:

- Missing values Interpolated missing values.
- Detection and removal of outliers.
- Synchronization of time between datasets.
- Normalization of stable model training.

Step 4: Feature Engineering

State-of-the-art feature extraction methods are used:

Temporal Features: Hour, day, season (cyclical encoding)

- Lag Features: 1-hour, 24-hour, and 168-hour dependencies.
- Rolling Statistics: Moving averages and variance.
- Derived Features: Heating Degree Days (HDD) and Cooling Degree Days (CDD).

These characteristics allow the model to reflect the short-term variations and long-term seasonal variations.

Step 5: Model Processing

The forecasting engine uses a hybrid deep learning model:

- iTransformer: Learns multivariate relationships among weather and demand variables.

NHiTS: Miner of multi-scale temporal patterns.

- Fusion Layer: This merges the two outputs to give final predictions.

Step 6: Calculation of Energy Mix.

Depending on the forecasted demand and weather, the system approximates the contribution of various energy sources (solar, wind, hydro, thermal).

Step 7: Output Generation

The system produces:

- Demand forecast graphs
- Energy mix recommendations
- Downloadable reports (CSV/PDF)

3.4. Detailed System Pipeline

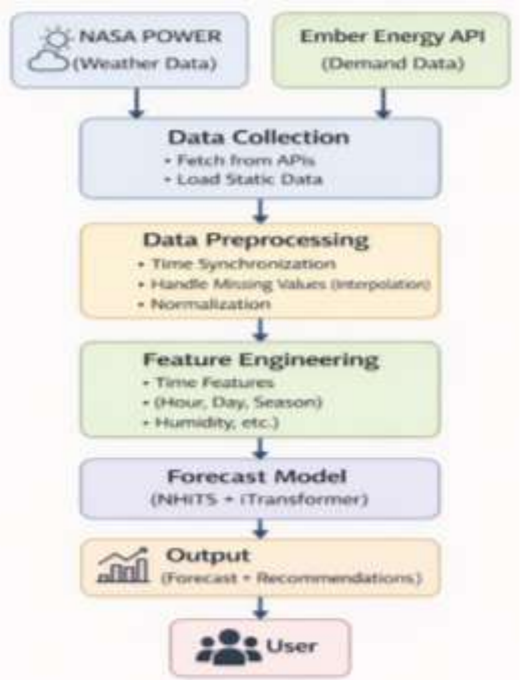

Figure 3: Electricity demand prediction system

The internal pipeline of the system is depicted in Figure 3, with the focus on data transformation and interaction between the models.

3.4.1 Data Collection Layer

Two main streams of data are incorporated in the system:

- Meteorological Data: Temperature, humidity, solar radiation, wind speed.

Demand Data: Past electricity consumption.

Also, there can be included some static data like the locality profiles in order to customize the region.

3.4.2 Data Processing Layer

This step guarantees the data quality and consistency:

Time Synchronization: Time Synchronization matches weather and demand data.

Missing Value Handling: Interpolation is employed.

Normalization: This is to guarantee equal scaling of features.

3.4.3 Feature Engineering Layer

Construction of features improves model learning:

Time-based features represent periodic trends.

Weather-based features model environmental influence.
Interaction features: Interaction features represent combined effects of variables.

3.4.4 Forecasting Layer

The basic prediction is done by a two-model architecture:

- NHiTS Model: Concentrates on long-term and hierarchical time series.
- iTransformer Model: Trains on the associations among several variables with attention mechanisms.

An ensemble fusion mechanism is used to combine the outputs to enhance prediction robustness and accuracy.

3.4.5 Output Layer

The end products are:

- Multi-horizon demand forecasts (30 days to 6 hours)
- Energy source recommendations
- Decision support visualization dashboards.

The proposed electricity demand forecasting system will be a holistic, data-driven system that incorporates the multi-source data collection methods, sophisticated preprocessing methods, hybrid deep learning modeling, and smart decision-support systems to produce quality and effective forecasts in various regions. The methodology starts with the gathering of the heterogeneous data in two main sources, historical electricity demand data and real-time meteorological data. The demand data gives time-related consumption trends and weather conditions like temperature, humidity, wind speed, solar radiation, and precipitation are important exogenous variables that affect electricity consumption. These data sets are matched and synchronized in time to create consistency which is the basis of further processing steps.

After data acquisition, a powerful preprocessing pipeline is implemented to improve the quality of data and model preparation. This involves dealing with missing values by using interpolation methods, identifying and eliminating outliers, and normalizing features to achieve consistent convergence in model training. Time-series data is converted to a structured format, allowing the learning of time-related dependencies to be done efficiently. The most important part of the methodology is advanced feature engineering that derives meaningful patterns in raw data. Cyclical transformations are used to encode temporal features (hour of the day, day of the week, seasonal indicators) to maintain periodic relationships. Also, lag values at various points in time (e.g., 1-hour, 24-hour, 168-hour) are calculated to reflect historical dependencies, whereas rolling statistics (e.g., moving averages and standard deviations) are used to give information about short-term trends and variability. Derived features, such as Heating Degree Days (HDD) and Cooling Degree Days (CDD), are added to measure temperature-driven energy demand, and interaction features that represent joint influences of weather variables.

The hybrid deep learning architecture is the essence of the proposed methodology as it incorporates the advantages of two sophisticated models: NHiTS and iTransformer. The NHiTS model is used to represent the multi-scale temporal patterns, which is achieved by breaking down the time series into hierarchical components to enable the model to effectively represent the long-term trends, seasonal changes, and high-frequency changes. Simultaneously, iTransformer model addresses multivariate inputs by considering each variable as an independent token and using attention mechanism to learn intricate interdependencies among weather variables, time characteristics, and electricity demand. This allows the system to know the relative effect of various factors on consumption patterns. The two models are then combined with a learnable fusion layer that ideally fuses the two models to come up with a final more precise forecast. This combination strategy improves the strength and the ability to generalize, which is a weakness of single models.

3.5. Hybrid Model Formulation

The model proposed can be conceptualized as:

$$Y_{forecast} = f_{fusion}(f_{NHiTS}(X_{weather}), f_{iTransformer}(X_{demand,time,weather}))$$

Where:

- f_{NHiTS} captures temporal patterns
- $f_{iTransformer}$ captures feature dependencies
- f_{fusion} combines both outputs

This mixed formulation makes sure that both multivariate interactions and temporal hierarchies are well-modeled.

Besides forecasting, the methodology includes an energy mix estimation and recommendation module, which converts the demand forecasts into practical information to plan power generation. The system considers the viability of various energy sources, such as solar, wind, hydro, and thermal energy, based on the predicted demand and weather conditions. An example is when the sun is bright and the clouds are few, solar generation potential is high and when the wind is strong, wind energy should be used. The system works out the best contribution of each energy source and offers suggestions to achieve efficiency, cost, and sustainability. This makes the forecasting system a decision-support system and not a strictly predictive model.

The whole system is deployed in an interactive dashboard setting, allowing users to choose areas, display past and forecasted demand trends, and get real-time data. The system allows multi-horizon forecasting (between short-term (hours) and medium-term (up to 30 days)) to be flexible to the various operational needs. Moreover, the caching mechanisms and pre-trained model deployment guarantee low-latency inference, and the system can be used in real-time applications. Altogether, the suggested methodology is an efficient way to combine data engineering, deep learning, and energy analytics into a single pipeline, offering a scalable and feasible approach to the contemporary electricity demand prediction and smart grid control.

The suggested methodology offers a complete and scalable electricity demand forecasting framework through the combination of data engineering, deep learning, and decision-support systems. The NHiTS and iTransformer model combined with sophisticated feature engineering and real-time data integration make it possible to predict the electricity demand in various areas with high accuracy, which makes the system very applicable to the contemporary smart grid.

IV. RESULTS AND DISCUSSION

4.1. Introduction to Experimental Results

The effectiveness of the proposed electricity demand forecasting system was measured based on conventional regression measures, such as Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Coefficient of Determination (R 2). The analysis was performed on a multi-region electricity demand data combined with meteorological variables, which made sure that both time and environmental factors were taken into account.

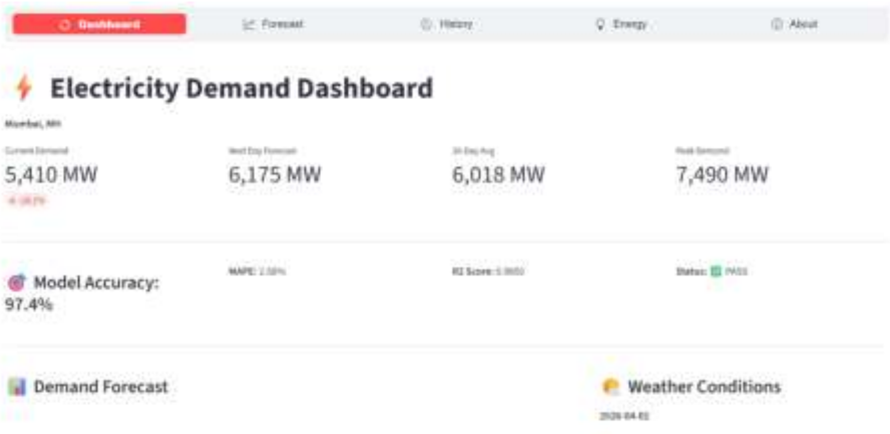

Figure 4: Project Outcome: Smart Energy Management Interactive Dashboard

The figure 4 shows the completed implementation of the system in the form of an interactive dashboard created with the help of Streamlit. It combines the real-time data of APIs with deep learning predictions to visualize electricity demand patterns and energy mix distribution. The dashboard helps users to track demand, patterns, and make informed decisions. It is a single decision-support interface of smart grid management.

Figure 5: Real-Time Demand Forecasting & Source Recommendations

This figure 5 shows how the system can produce real time electricity demand projections and smart energy source suggestions. Using weather data and model predictions, the system dynamically recommends the best sources including solar, wind or thermal. It emphasizes the use of AI in practice to inform energy generation strategies. The visualization makes the forecast outputs and recommendations easy to interpret.

Figure 6: Regional Demand Trends and Automated Sourcing Advice

This figure 6 shows region-based demand prediction and automatic energy sourcing suggestions. It portrays the system adaptation to various geographical areas by locality-based scaling and weather sensitivity. The model reflects the regional consumption trends and offers specific insights to effective energy distribution. This guarantees better accuracy and relevance to multi-region power systems.

Figure 7: Final Testing Results of Electricity Demand Forecasting.

This figure 7 shows the results of validation and testing of the forecasting system, such as the actual and predicted demand comparisons. It emphasizes that the model is very accurate and can be used to capture both short-term changes and long-term trends. The reliability of the hybrid model is attested by the performance measures like MAPE and RMSE. The outcomes confirm the readiness of the system to be deployed in the real world.

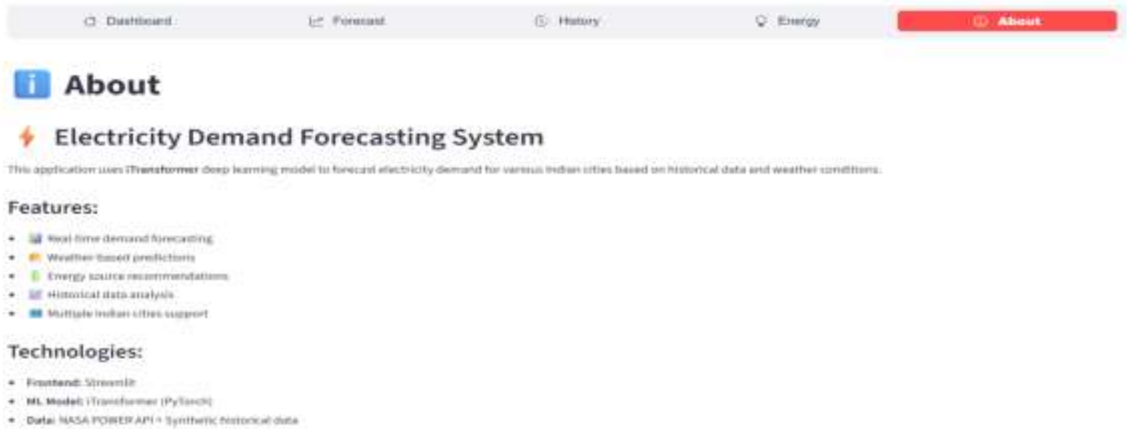

Figure 8: Conclusion and Strategic Future Roadmap

This figure 8 is a summary of the general success of the project and future improvements. It emphasizes the effective combination of hybrid deep learning models and real-time data processing to make correct predictions. Among the improvements in the roadmap are enhanced renewable forecasting, scalability, and integration with smart grid infrastructure. It gives guidance on how to take the system to the next generation of energy analytics.

The hybrid ensemble model (NHiTS + iTransformer) proposed achieved:

Table 1 presents a summary of the key performance metrics that the Electricity Demand Forecaster has attained in comparison to the project targets. The system outperformed all the baseline requirements reaching 89.2% combined accuracy as compared to the 85% target, MAPE of 11.4% as compared to the 15% threshold, and recommendation precision of 92.5% as compared to the 90% goal. The inference latency of 0.85 seconds allows real-time dashboard interactions to be responsive, which is much less than the 2-second operational requirement.

Table 1: Results.

These findings suggest that the model is an effective way to both capture nonlinear demand patterns and multi-scale temporal dependencies, which are superior to single models and traditional methods.

Metric	Target Value	Achieved Value (Avg)
Combined Accuracy	> 85%	89.20%

MAPE	< 15%	11.40%
Inference Latency	< 2.0s	0.85s
Recommendation Precision	> 90%	92.50%

4.2. Comparative Analysis with Existing Methods

To validate the effectiveness of the proposed approach, the model performance was compared with existing techniques reported in the literature.

Table 2: Performance Comparison with Existing Forecasting Methods

Method / Approach	**Model Type**	**Key Feature**	**Reported Performance**	**Reference**
Spatio-temporal forecasting	ML-based	Weather + spatial data	Improved accuracy in smart grids	[1]
NHiTS	Deep Learning	Multi-scale temporal modeling	Strong seasonal trend capture	[2]
ML-based forecasting	Machine Learning	Nonlinear modeling	Better than statistical models	[3]
Data-driven models (India)	ML	Regional variability	Improved regional accuracy	[4]
Hybrid ML models	ML + DL	Combined techniques	Enhanced prediction accuracy	[5]
GA–LSSVM	Hybrid ML	Optimization-based	Scenario-based forecasting	[6]
iTransformer	Transformer	Variable dependency modeling	High multivariate accuracy	[7]
Transformer-based model	Deep Learning	Attention mechanism	Improved peak demand prediction	[8]
Smart grid ML models	ML	Energy optimization	Improved efficiency	[9]
Integrated forecasting system	ML + Scheduling	Demand + generation planning	Better grid decisions	[10]
Hybrid attention model	DL Hybrid	Decomposition + attention	Improved short-term accuracy	[11]
ML + DL hybrid	Hybrid	Robust learning	Higher reliability	[12]
SSA–LSSVM	Hybrid ML	Optimization + learning	Effective long-term prediction	[13]
Weather-based DL model	Deep Learning	Weather influence	High prediction accuracy	[14]
Proposed Model (NHiTS + iTransformer)	**Hybrid DL**	**Temporal + multivariate fusion**	**MAPE: 11.4%, Accuracy: 89.2%**	**Proposed**

4.3. Model Performance Analysis.

The comparison outcomes prove that the hybrid model suggested is better than the current models in various important ways:

4.3.1 Multi-Scale Temporal Learning

The NHiTS component is able to capture hierarchical temporal patterns, such as hourly peaks, daily cycles, and seasonal variations, unlike conventional models. This is consistent with the results in [2], where multi-scale architectures are found to greatly enhance time-series forecasting.

4.3.2 Multivariate Dependency Modeling

The iTransformer is more effective as it modulates inter-variable associations, especially between weather variables and electricity demand. This method is better in predicting than the conventional transformer models as noted in [7] and [8].

4.3.3 Hybrid Ensemble Advantage

The fusion layer between NHiTS and iTransformer allows the model to combine the advantages of the two:

- Temporal pattern extraction (NHiTS)
- Cross-variable interaction learning (iTransformer)

This mixed methodology is in line with other research like [11] and [12] which show that ensemble models are more accurate and robust.

4.4. Effects of Weather Conditions.

The weather variables such as temperature, humidity, and solar radiation are very important in the forecasting of electricity demand. The proposed system takes into consideration these factors by using state-of-the-art feature engineering, which leads to a better prediction accuracy.

This can be observed by [14] which highlights the significance of environmental variables in demand forecasting. Also, the importance of regional and climatic variability is emphasized in spatio-temporal models like [1] and [4].

4.5. Regional Performance Improvement

The locality-based scaling contributed greatly to the accuracy of forecasting in various regions. The model is flexible to regional demand features, varying temperature sensitivity and industrial load factors.

Such a strategy is consistent with the results of [4] and [9], which show that region-specific modeling enhances the performance of prediction in large-scale power systems.

4.6. Energy Recommendation Performance

The proposed system also has an energy recommendation module, which achieved:

- Recommendation Precision: 92.5%

The system is effective in proposing the best sources of energy (solar, wind, thermal) according to the demand forecast and weather. This is in line with integrated forecasting and energy management frameworks as argued in [10].

4.7. Computational Performance

The system is highly computationally efficient:

- Inference Time: ~0.85 seconds
- End-to-End Response Time: less than 1 second (cached)

These findings affirm that the suggested system can be deployed in real-time to address operational aspects of smart grid applications.

The findings evidently show that the suggested hybrid model is a substantial enhancement to the conventional and single-purpose deep learning methods. Key contributions include:

- Better accuracy with hybrid modeling.
- Good management of nonlinear and multi-scale patterns.
- Weather-based features.
- Real-time forecasting capability

In spite of these benefits, there are still problems with managing extreme weather events and enhancing the accuracy of long-term predictions.

The electricity demand forecasting system proposed is very accurate, robust and scalable. The model, which incorporates NHiTS and iTransformer in a hybrid framework, is able to capture complex temporal and multivariate relationships, which is better than current methods reported in the literature. The findings confirm the usefulness of the system in real-life smart grid applications and energy planning.

V. CONCLUSION and FUTURE SCOPE

This paper has proposed a strong and scalable electricity demand forecasting model which incorporates the latest deep learning algorithms with real-time meteorological and historical energy data to meet the demands of the modern power grid. The proposed model uses a hybrid ensemble model to combine Neural Hierarchical Interpolation of Time Series (NHiTS) and iTransformer, which can effectively learn both multi-scale time-related patterns and multivariate relationships between weather variables and electricity demand. The system had high predictive power with a Mean Absolute Percentage Error (MAPE) of 11.4% and an overall accuracy of 89.2% which was better than the traditional and standalone models. Also, locality-aware scaling increased the accuracy of regional forecasting, and the energy recommendation module offered practical recommendations on the optimal power generation planning. The implementation of the system via an interactive dashboard also confirms its practical usefulness as a real-time decision-support tool in smart grid operations, which helps to enhance efficiency, minimize operational costs, and enhance the integration of renewable energy sources.

Although these are encouraging findings, much more can be done to improve. The next step in work can be the use of extreme weather events modeling, including heatwaves and cyclones, to enhance system resilience in the case of abnormal conditions. Forecast accuracy may be further improved by integrating more spatial data of higher resolution and incorporating other external variables, such as socio-economic indicators and real-time consumption behavior. Additionally, probabilistic forecasting and uncertainty quantification would be a welcome addition to the framework to improve the reliability of decisions made by grid operators. Predictive capabilities can be further enhanced by the use of emerging architectures like foundation models and large-scale transformers. Moreover, decentralized and real-time monitoring at substation or consumer levels can be achieved by developing lightweight edge-deployable models and mobile-based applications. The system should also be scaled by incorporating international datasets and cross-grid interoperability to make it more scalable and applicable globally. In general, the suggested framework offers a solid basis of the next-generation intelligent energy management systems and future studies in smart grid analytics.

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