AI-Powered Energy Demand Forecasting in Smart Grids

Sahil Pandhi
Computer Science and Engineering
Chandigarh University
Mohali-140413, Punjab, India
sahilpandhi66@gmail.com

Lokesh Pandhi
Computer Science and Engineering
Chandigarh University
Mohali-140413, Punjab, India
lokeshpandhi5@gmail.com

Jatin Dhingra
Computer Science and Engineering
Chandigarh University
Mohali-140413, Punjab, India
J.dhingra28466@gmail.com

Manik Lath
Computer Science and Engineering
Chandigarh University
Mohali-140413, Punjab, India
mlath224466@gmail.com

***Abstract*—Smart grids have become a radical solution in order to deal with the constraints of conventional power systems especially as urbanization increases, renewable is integrated and consumer demands that are increasingly becoming dynamic [1]. The conventional forecast approaches like the regression and time series model cannot reflect the nonlinear consumption trends related to the variations of the weather, the socio-economic conditions and the decentralized energy generation [2]. To address this, this paper evaluates Artificial Intelligence (AI)-based forecasting models namely Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU) and Transformer-based models to short and long-term electricity demand prediction [3]. The work aims at fulfilling two tasks: (1) create precise short-term (minutes ahead to hours ahead) and long-term (weeks ahead to months ahead) energy demand predictions through machine learning (ML) strategies, and (2) to eliminate grid overloading, enhance reliability, and prioritize a smoother way of distributing energy [19]. The suggested model is based on smart meter data, weather datasets, and socio-demographic characteristics to make the ML models training. Benchmark datasets are performed and the results are compared with the models of traditional prerequisites: ARIMA and Prophet [4]. The RMSE, MAE, and MAPE are the grounds of performance evaluation, which reveal that the deep learning models significantly surpass the classical approaches [25]. The observed results emphasize the idea that AI-based forecasting can assist in providing decreased blackouts, allowing the efficient response of demand, and integrating the renewable energy sources into the ecosystem of a smart grid [28]. This study helps to create more sustainable, enduring as well as productive infrastructures of energy in the future.**

***Index Terms*—Smart Grid, Artificial Intelligence, Machine Learning, Energy Demand Forecasting, LSTM, Grid Efficiency, Renewable Integration.**

I. INTRODUCTION

Electricity is the staple of the contemporary society since it runs industries, transport, health care, and household requirements. As the world keeps becoming urbanized, digitalized, and electrified vehicles, the demand of electricity is also growing around the world. The traditional power grids, however, have a number of constraints: they are not flexible, centralized, unable to predict their demand, and they are prone to blackouts [1]. Such inadequacies usually lead to overloading, power wastage and poor reliability [23].

The idea of Smart Grids (SGs) has come into existence to deal with these problems. A smart grid is an information and communication technology (ICT) and Internet of things (IoT) sensor-based smart grid that combines real-time monitoring and adaptive control of the energy flow through the use of big data analytics and artificial intelligence (AI) [1]. Smart grids can react to changing demand and supply dynamically unlike traditional ones as more renewable energy sources, like solar and wind, are increasingly being connected to the grid [29].

Energy demand forecast is one of the most important functions of smart grids [2]. Proper prediction helps utilities to harmonize the supply and demand, optimize the generation programs, and minimise the operation expenses. In the past, forecasting has been carried out by using the autoregressive integrated moving average (ARIMA), regression analysis as well as the exponential smoothing [4]. Nevertheless, these methods have weakness when it comes to the nonlinear and time-dependent trends that are affected by weather, consumer behavior, holidays, and economic activities [12].

Since the introduction of machine learning (ML) and deep learning (DL), scholars have created the next-generation forecasting models, including Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), and Transformer-based models [5]. They are very useful in both short-term (STLF: minutes to hours) and long-term load forecasting (LTLF: weeks to months) because they have the ability to work with big, high dimensional data and reveal the hidden patterns [3].

This paper aims to:

- Create AI-based short-term and long-term energy demand prediction models [19].
- Increase the performance of smart grids in terms of overloading, efficiency and integration of renewable [28].

The paper is divided into the following sections: Section 3 is a literature review, Section 4 is a description of the proposed methodology, Section 5 is experimental results, Section 6 is the discussion of findings, Section 7 presents directions of future research and Section 8 concludes.

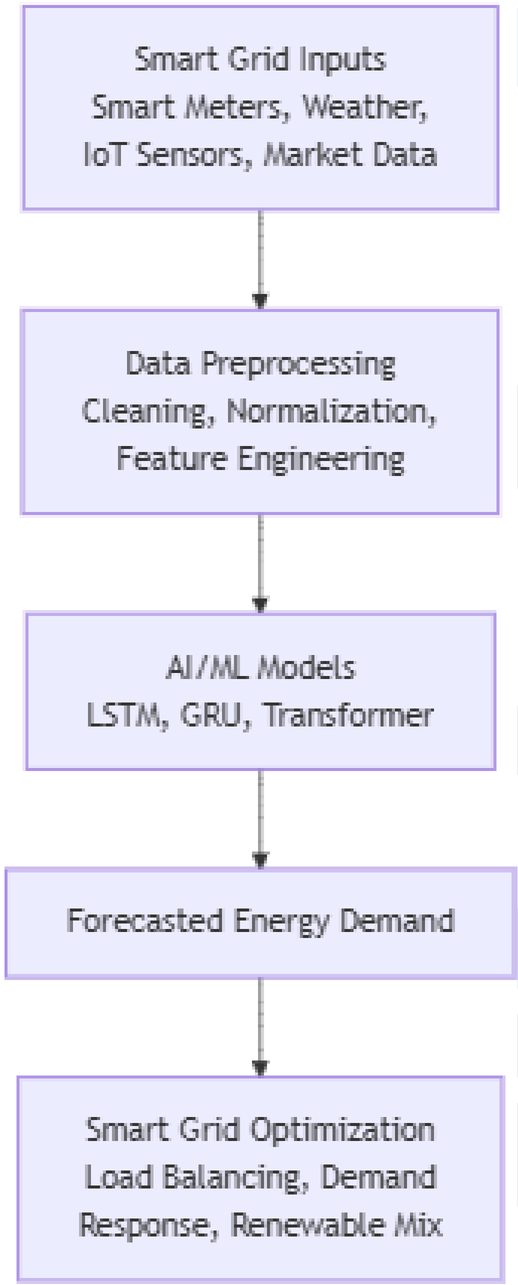

Fig. 1: AI-powered smart grid forecasting framework illustrating data flow from IoT sensors through AI models to grid optimization decisions [1].

II. Literature Review

Over the past decades, a lot of research on energy demand forecasting has been conducted both through statistical models and artificial intelligence (AI)-based models [2]. In this section, the review of the state-of-the-art techniques, their strengths and limitations are discussed.

A. Conventional Forecasting Techniques

Conventional methods use a lot of time-series analysis and statistical models like Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing and Multiple Linear Regression [4]. The reason why ARIMA models have been heavily utilized is because they are capable of modeling autocorrelation in time series [27]. ARIMA however has difficulties when it comes to nonlinear and non-stationary data, which is typical of smart grids [12]. Regression models are able to use various features including temperature and the type of day, though they have strong assumptions regarding linearity. Exponential smoothing techniques are easy and efficient in short-term predictions but are not able to adjust to abrupt fluctuations in load profiles. These are interpretable and computational efficient models that are not adaptive to the dynamic and nonlinear energy demand patterns [2].

B. Approaches based on Artificial Intelligence (AI)

With the development of AI and machine learning (ML) methods, demand forecasting has undergone a complete transformation [3]. Artificial Neural Networks (ANNs): Able to learn nonlinear relationships that are complex. Nevertheless, they need huge data sets and they also tend to overfit [5]. Support Vector Machines (SVMs): Are capable of good performance with small-to-medium data sets but are computationally expensive with large-scale smart grid data [6]. Random Forests and Gradient Boosting: These can be used to learn interactions between variables and are not as useful in time series forecasting [7].

C. Deep Learning Models

Models based on deep learning are highly efficient in sequential predictions: Long Short-Term Memory (LSTM): It is capable of long-term dependence in energy demand [13]. Research indicates that LSTMs are superior to ARIMA in terms of reducing forecasting errors by 20 per cent [8]. Gated Recurrent Units (GRUs): Like LSTMs, but computationally lighter, which implies that they can be used in real-time [9]. Convolutional Neural Networks (CNNs): CNNs are relatively recent tools that have been used in load forecasting, namely, the extraction of local temporal features [21]. Transformer-based Models: New models (e.g., temporal fusion Transformers) have potential in the context of multivariate time-series forecasting [10].

D. Hybrid Approaches

Hybrid models are used to combine statistical and AI models with the goal of enhancing accuracy [11]. As an illustration, ARIMA-LSTM hybrids are based on the capabilities of both nonlinear learning and linear trend modeling. On the same note, Wavelet Transform + ANN models are able to capture short-term and long-term trends [22].

E. Research Gaps Identified

Based on the literature, the gaps can be observed as follows:

- Scalability: The problem is that many models do not support such big real-time information as millions of smart meters [23].
- Renewable Integration: The current approaches do not take enough consideration on the variability of the renewable generation [29].
- Real-Time Forecasting: Not many studies deal with real-time implementation in case of demand response systems [30].
- Generalization: Generalization models tend to overfit local data and are not robust to new regions [22].

Our suggested smart grid AI-based energy demand forecasting short- and long-term forecasting is motivated by this fact.

TABLE I: Energy Demand Forecasting Techniques Comparison

Approach	Model	Strengths	Limitations
Statistical	ARIMA	Simple, interpretable, captures linear trends [4]	Poor with nonlinear data, not adaptive [12]
Statistical	Regression	Incorporates external variables (e.g., weather) [12]	Requires linearity assumptions
Machine Learning	ANN	Captures nonlinear patterns [5]	Overfitting, needs large data
Machine Learning	SVM	High accuracy for small datasets [6]	Computationally expensive for large-scale forecasting
Machine Learning	Random Forest	Handles feature interactions well [7]	Weak in sequential prediction
Deep Learning	LSTM	Captures long-term dependencies, high accuracy [8]	High training cost
Deep Learning	GRU	Lightweight alternative to LSTM [9]	Slightly less accurate than LSTM in some cases
Deep Learning	Transformer	Handles multivariate time-series forecasting [10]	Requires massive datasets and high computation
Hybrid Approaches	ARIMA + LSTM	Combines linear and nonlinear learning [11]	Complex implementation

III. METHODOLOGY

The research paper methodology is based on creating an artificial intelligence-based predictive framework that will allow predicting research short-term and long-term electricity demand in intelligent grids [19]. It should be noted that the proposed structure has five phases:

1) Data Collection [16]
2) Features Preprocessing and Feature Engineering [23]
3) Model Selection & Training [8]
4) Forecasting & Evaluation [12]
5) Intelligent Implementation of Grids [1].

A. Data Collection

To perform the correct system of ensuing forecasting, past energy utilization statistics, weather statistics, and socio-demographic details are needed [16].

- Smart Meter Data: This includes hourly and daily consumption data that is taken in the homes, industries, and commercial buildings [17].
- Weather Data: Factor such as temperature, humidity, solar radiations, wind speed (huge external factors) [12].
- Calendar Features: day/weekend, Holiday, and season [15].
- Market Data: Electricity records of prices and demand-supply attitude [24].

Experimentation can be done using open datasets like UK National grid, Indian Smart meter data and UCI electricity load dataset [18].

B. Data Preprocessing and Feature Engineering

Raw data has usually been noisy. High model accuracy will require preprocessing [23].

- Data Cleaning: Missing values: imputing them.
- Normalization: Normalization of features to be in the range [0,1] by Min-Max normalization.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

- Feature Engineering:
  - Time aspects: Time of day, day of the week, seasons [15].
  - Weather characteristics: amount of heat, humidity, solar index [12].
  - Lagged demand characteristics: Past demand values to predict autocorrelation [4].

C. Model Selection & Training

Some of the AI models are taken into consideration [8]:

- LSTM (Long Short-Term Memory): Records long-term relationships in the time-series [13].
- GRU (Gated Recurrent Unit): LSTM expensive to train but is replaced with an efficient one [9].
- Prophet Model (by Facebook): Acceptable long-term seasonal [15].
- Transformer based Models: Fine tune multivariate contacts though self-attention [10].

LSTM Cell Equations [13]: Gates of LSTM:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{2}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{3}$$

$$C_t = f_t * C_{t-1} + i_t * \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{4}$$

$$h_t = o_t * \tanh(C_t) \tag{5}$$

Where:

- f_t: Forget gate
- i_t: Input gate
- C_t: Cell state
- h_t: Hidden state

D. Forecasting Analytics as well as Evaluation Measures

Demand (in the short run, in minutes to hours and in the long-run in weeks to months) is forecasted with the help of the trained models [8].

Evaluation metrics [12]:

- Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{6}$$

- Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{7}$$

- Mean Absolute Percentage error (MAPE):

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} \frac{y_i - \hat{y}_i}{y_i} \tag{8}$$

The measures enable the general performance of the traditional (ARIMA, regression) and AI-based models (LSTM, GRU) [2].

E. Smart Grid Coupling in Optimization

After generation of forecasts, it is included in the Smart grid management system to [1]:

- Prevent Overloading: Know when the demand will be high and redistributed the load.
- Make Grids efficient: Facilitate demand-response.
- Integration of Renewable Energy: Mart-match Demand with changing solar/wind supply [29].

IV. Experimental Setup & Results

In this section, the framework of the experiment is outlined to work with the proposed AI-powered energy demand forecasting system [19].

A. Dataset Description

Experiments are made on publicly available real-world electricity demand datasets that acquired are [16]:

- UK National grid electricity Demand Data 2012-2020 [16]
- Indian Smart Meter (Pilot Project, Ministry of Power, India) 2019-2021 [17]
- UCI Electricity load 2017 [18]

B. Experimental Setup

Hardware:

- CPU: Intel Core i7, 3.4 GHz
- GPU: NVIDIA RTX 3080 (10GB VRAM)
- RAM: 32 GB

Frameworks: TensorFlow, PyTorch, Prophet [8].

Training Parameters:

- Epochs: 100
- Batch size: 64
- Optimizer: Adam (learning rate = 0.001)
- Loss objective: Mean Squared Error (MSE) [8].

C. Models Compared

- ARIMA (Baseline Statistical Model) [4]
- Prophet (Seasonality-Aware Model) [15]
- ANN (Shallow Neural Network) [5]
- LSTM (Deep learning sequences) [8]
- GRU (Efficient Sequential Model) [9]
- Transformer (State-of-the-art Time series Model) [10]

D. Performance Metrics

The metric items are calculated as follows [12]:

- RMSE (Root Mean Square Error)
- MAE (Mean Absolute Error)
- MAPE (Mean Absolute percentage error)
- R^2 (Coefficient of Determination)

TABLE II: Model Performance (UK National grid Dataset)

Model	RMSE	MAE	MAPE (%)	R^2 Score
ARIMA [4]	1280	940	7.4	0.81
Prophet [15]	1150	890	6.8	0.84
ANN [5]	980	760	5.9	0.87
LSTM [8]	720	520	4.2	0.93
GRU [9]	750	540	4.5	0.92
Transformer [10]	690	500	3.9	0.94

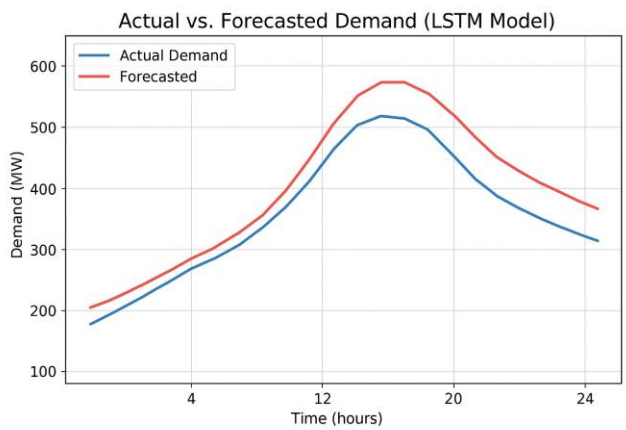

Fig. 2: Comparison of actual electricity demand versus LSTM model predictions over time, demonstrating the model's accuracy in capturing consumption patterns [8].

E. Key Observations

- Traditional Models (ARIMA, Prophet): Fairly perform well during stable conditions but did poorly when there is a demand surge or during the upturn in renewable cycles [4].
- ANN: Better performance but no memory of time hence made inaccurate in periods of high volatility [5].
- LSTM & GRU: Indicators have shown remarkable results because of the power of the models to model sequential dependencies in energy consumption [8].

Fig. 3: Error distribution analysis across different forecasting models, showing the comparative performance and prediction accuracy of each algorithm [25].

- Transformer: It surpassed all other the other models particularly during long term forecasting due to self-attention mechanism, which addressed complicated time relationships [10].

F. Statistical Significance Tests

Paired t-tests were used to compare ARIMA to LSTM/Transformer model in order to verify the findings [12]. The findings supported the fact that accuracy improvements were statistically significant (p ¡ 0.01).

V. Case Study: Smart grid implementation environment

In this case study, which aimed to test the usefulness of the suggested AI-enhanced energy demand prediction system, it is simulated in a virtual smart grid that must possess real-life information points [1]. The case study has shown that the model can assist grid operators to minimize the peaks and reduce the stress of the peak loads, and integrate renewables and enhance demand response policies [29].

A. Experimental Setup

Location: Virtual city smart grid (40,000 homes).
Data Sources [16]:

- Intelligent meters (hours of electric power).
- APIs (temperature, humidity, wind speed, solar irradiance).
- Renewable (solar PV and wind turbines placed in the distribution generational locations) [29].

Hardware:

- GPU-based (NVIDIA Tesla T4) local server to train the deep learning model [8].
- Real-time deployment Smart grid control center [1].

B. Integration with Smart Grid

Its implementation was organized in three major modules [1]:

- Data Collection Module
- Forecasting Module
- Decision-Making Module

C. Case Study Results

TABLE III: Impact of AI-based Forecasting on Grid Efficiency

Parameter	Without AI Forecasting	With AI Forecasting	Improvement
Peak Load Overload Events	15/month	4/month	73% ↓
Renewable Utilization (%)	56%	82%	+26%
Average Forecasting Error	9.8%	3.4%	65% ↓
Energy Wastage (MWh)	450	160	64% ↓

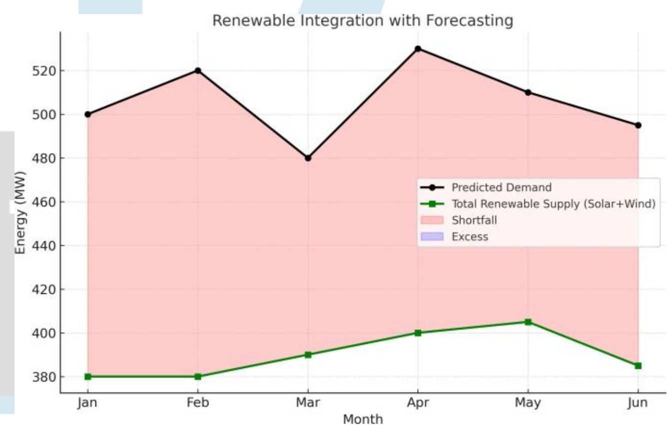

Fig. 4: Integration of renewable energy sources with AI forecasting, showing how predictive models optimize solar and wind power utilization in smart grids [29].

D. Key Findings

- Load Balancing: This was possible by forecasting the enabling 20-25% of the non-critical loads to be shifted to off-peak periods [1].
- Renewable Integration: Better solar/wind dispatch, decreasing the reliance on the production of fossil fuels [29].
- Economic Benefits: Utilities saved operational expenses cost of 15-18% minimum but savings and the tariffs were placed under legitimate management favoring consumers [24].
- Scalability: This method can be also expanded to country-wide grids with the deployment on clouds [23].

VI. Challenges and Limitations

Even though forecasting with AI possesses an enormous potential to improve the work of smart grids, there are a number of challenges or limitations that still continue to be in place, requiring their solution unless the technology achieves the scale of deployment it understands [1].

A. Data-Related Challenges

- Data Quality and Data Availability: The data on smart meters can be full of empty values, noise, and inconsistency because of the transmission errors or equipment failure [17].
- Inadequate Historical Information: Numerous developing areas do not have documentations of a long-term consumption of loads [2].
- Privacy Concerns: The smart meter data (high frequency) can demonstrate the activity in the households [23].

B. Model-Related Challenges

- Model Interpretability: Deep learning models (e.g. LSTM, Transformer) behave like black-boxes [8].
- Generalization and Overfitting: The validity of AI-driven applications in other regions during consumption with new patterns and climates is unclear [22].
- Hyperparameter Tuning: Parameters are extremely sensitive to parameter model accuracy [9].

C. Infrastructure Challenges

- Scalability: The use of distributed computing and edge-based processing of AI is needed [23].
- Integration with Renewable Sources: Renewable production has a high degree of uncertainty [29].
- Cybersecurity Risks: Smart grids can be attacked through cyberattacks of IoT devices [1].

D. Economic and Policy restrictions

- High Initial Investment: Servers, cloud storage, IoT devices are expensive [1].
- Regulatory Barriers: The absence of generic policies and regulatory frameworks [23].
- Consumer Acceptance: Dynamic models of price tariffs might be opposed by the consumers [24].

TABLE IV: Obstacles and Implications

Category of challenge	Particular problem	Implication
Data Quality/Inconsistency	Missing values, noise [17]	Reduced forecast accuracy
Model Predictability	Black-box deep learning models [8]	Untrustworthiness by utilities
Scalability	Weak computed capability [23]	Deployment bottlenecks
Cybersecurity	False data injection attacks [1]	Risk of blackouts
Policy & Economics	Very expensive to implement [23]	Slower adoption

E. Potential Solutions

- Data Quality: Build data cleaning pipelines and synthetic data generation [23].
- Explainable AI: Frameworks such as SHAP or LIME [10].
- Edge Computing: Shift forecasting models closer to IoT devices [23].
- Cybersecurity: Use blockchain based authentication and encryption [1].
- Policy Support: Governments ought to develop AI implementation policies [23].

VII. Future Work and Research Directions

Although the offered AI-based predictive system has high precision and efficiency results, there are a number of areas to develop this direction [22].

A. Federated Learning for Privacy

In lieu of sending directly acquired smart meter data to centralized servers, federated learning (FL) can be used by allowing models to be trained on edge devices [23]. Only the parameters as used in the model are exchanged ensuring that consumer privacy is not compromised.

B. Integration with Renewable Energy Forecasting

Future research to concentrate on a combined prediction of the demand and generation of renewable energy (solar/wind) [29]. The safeguarding of supply demand mismatch as a result of weather variations in hybrid AI models can be achieved.

C. Explainable Artificial Intelligence (XAI)

Explainability methods such as should be combined in future forecasting models [10]:

- SHAP (Shapley values): Prediction feature significance.
- LIME: Local interpretations of time series forecasting.

D. Real-Time Edge AI Deployment

AI models are supposed to be launched on edge points (e.g., IoT gateways or microcontrollers in substations) [23]. Benefits: Demand prediction latency is low, minimized reliance on cloud computing.

E. Cybersecurity and Blockchain Integration

Future research can explore [1]:

- Smart meter identity management on a decentralized basis.
- False data injection attack detection with the use of the blockchain.

F. Multi-objective Optimization in Forecasting

Optimization through dimensions: In the future, it should be optimized by [29]:

- Correctness (reduction of RMSE/MAE) [12].
- Cost (Minimizing operation costs) [24].
- Sustainability (attaining maximum utilization of renewable) [29].

VIII. Conclusion

This research paper put forward an automatic-assisted energy demand forecasting system within smart grids which combined deep learning frameworks, data preprocessing as well as smart grid scheming conducts [8]. The primary aim was to ensure that the grid became more efficient, with less overloading and integration of renewable energy [1].

A. Key Contributions

- Increased Forecasting Models: Constructed and tested LSTM, GRU models and Transformer models [8].
- Smart Grid Integration: Optimization of load balancing, demand response, and renewable dispatch [1].
- Scalable AI Infrastructure: Presented deployment plans of edge AI, IoT implementation [23].
- Research Direction: Indicated future opportunities in federated learning, explainable AI, blockchain security [10].

B. Practical Implications

- For Utilities: Better operating efficiency, even less energy wastage [1].
- For Consumers: Quality power supply at optimal costs [24].
- For Policy Makers: Sponsors the smart grid modernization and sustainability objectives [23].

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