

Research Article

IoT-Enabled Smart Metering to Enhance Energy Management for Day-Ahead Electricity Price Forecasting

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Abstract

In the realm of electricity generation, the output of generating units fluctuates throughout the day mirroring the dynamic nature of energy demand. While alterations on the generation side are limited post-installation, areas for intervention exist on the demand side to stabilize the demand curve. This research explores the fusion of day-ahead pricing models with demand forecasting mechanism employing smart meter technology in the electricity market. The investigation dives into the advantages of furnishing consumers with pricing information a day in advance and empowering to make informed decisions regarding their electricity consumption. Utilizing smart meters, which provide real-time consumption data, the study aims to refine the precision of demand forecasting. The outcome of the study allows consumers to optimize their electricity usage patterns in response to anticipated price fluctuations. The research thoroughly examines methodologies and technologies underpinning day-ahead pricing and demand forecasting, assessing their combined impact on consumer behavior and grid efficiency. Through a comprehensive analysis, this research contributes to understanding how the integration of day-ahead pricing and smart meter data can cultivate a more responsive and efficient electricity market, yielding benefits for both consumers and utilities.

Keywords

Day-ahead Pricing, Demand Forecasting, Smart Meter, IoT, Electricity Consumption, Grid Efficiency, Consumer Behavior, Energy Management

1. Introduction

This research studies the combination of demand forecasting techniques with day-ahead pricing models using data derived from smart meters. In day-ahead pricing, consumers are given one-day ahead price information providing information to adapt the consumption behaviors. This strategy seeks to motivate consumers to shift their use of electricity from peak times to off-peak times therefore flattening the

peaks in demand and increasing grid reliability. Smart meters are instrumental in this process as they provide detailed, real-time data on energy consumption. This data is crucial for improving the accuracy of demand forecasts, which, in turn, informs the day ahead pricing models. Utilities can predict the demand more precisely by leveraging real-time consumption data and set prices that encourage more efficient energy

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use.

The integration of IoT smart meters with advanced analytics has revolutionized demand side management (DSM), enabling accurate demand forecasting, real-time monitoring, and optimized energy consumption [1]. Game-theoretic models [2] and cloud-based AI [3] have further enhanced DSM capabilities. However, challenges persist in this sector including gaps in understanding long-term impacts and integrating day-ahead pricing with adaptive models [4]. Continued research is crucial for leveraging IoT technologies to optimize energy systems in diverse contexts, including Nepal [5].

IoT-enabled smart meters have the potential to transform energy management by giving real-time data and allowing for precise demand-side management. The capacity to estimate energy demand, improve consumption patterns and integrate dynamic pricing systems can result in smarter and more efficient power grids. However, issues such as practical implementation of these solutions and integration of advanced algorithms with current infrastructure still exist which hinders applicability. By solving these gaps particularly for Nepal, the study hopes to contribute to a future of sustainable and intelligent energy systems.

This study looks specifically at how effective the combination of day-ahead pricing and smart meter data is to enable different consumer behaviors that results in a more efficient grid. It looks at the technical processes behind implementing these systems and evaluates their broader impact on the energy market. By a comprehensive analysis this research strives to prove the possible advantages of combining day-ahead pricing methods and smart meter technology. The goal is to create a more responsive and efficient electricity market that benefits both consumers and utilities by fostering better energy consumption patterns and enhancing the stability of the power grid.

Results from this study will help to further our understanding of energy management and smart grid technology in the modern context, reaffirming the results that innovative solutions represent a vital part in tackling electricity market challenges. In addition to summarize information currently available, the work lays out directions for evolvement of future demand-side energy management tools.

2. Literature Review

The integration of IoT smart meters with advanced analytics, control, and optimization techniques is essential for enabling accurate demand forecasting, real-time monitoring, and effective electrical demand management [1]. However, there are still knowledge gaps in understanding the long-term impacts of IoT-based demand-side management systems and the development of advanced forecasting and optimization algorithms.

An evaluation of forecasting methods for residential electrical demand on a very small scale [4, 6]. The study focused

on the development and assessment of forecasting models for accurate prediction of residential electrical demand. The findings highlighted the potential for IoT smart meters to capture granular consumption data hence improving the accuracy of demand forecasting models for effective demand-side management.

A game-theoretic model predictive control approach for distributed energy demand-side management was also investigated [2]. The study proposed a control mechanism based on game theory to optimize the energy consumption patterns of distributed resources in the demand-side management process. The research findings underscored the significance of advanced control strategies enabled by IoT smart meters for effective demand-side management.

A comparison was made between day-ahead and intraday valuation of demand-side flexibility for photovoltaic and wind power systems [7]. The study emphasized the importance of accurate valuation of demand-side flexibility to enable effective integration of renewable energy resources. The research findings underscored the potential for IoT smart meters to provide real-time data on energy consumption patterns supporting the valuation of demand-side flexibility for improved electrical demand management. A study on optimized day-ahead pricing with renewable energy demand-side management for smart grids proposed a pricing optimization model to incentivize the integration of renewable energy resources and demand response programs in smart grids [8]. The research findings highlighted the potential for IoT smart meters to enable real-time monitoring and control of energy consumption advocating the implementation of optimized day-ahead pricing strategies for effective demand-side management.

The discipline of demand-side management research has morphed dramatically since its inception. A review was conducted on the impacts of demand-side management on electrical power systems [9]. The study highlighted the potential benefits of demand-side management in improving the overall efficiency and reliability of electrical power systems. The authors emphasized the need for advanced forecasting and optimization techniques to enable effective demand-side management strategies. The findings from this study underscore the importance of integrating IoT smart meters for accurate demand forecasting and management.

Similarly, the Asian Development Bank [10] has outlined a roadmap for smart metering in Nepal, emphasizing the benefits of situational awareness and improved demand-side management. These efforts demonstrate the importance of addressing knowledge gaps in developing advanced forecasting/optimization algorithms to enhance the efficiency and reliability of electrical demand management systems. Overall, the advances in China, India, and Nepal underpins the need for continued research and development to fully realize the potential of IoT-based DSM systems in enhancing electrical demand management.

Dynamic coordination among home appliances using mul-

ti-objective energy optimization for demand-side management in smart buildings was investigated [11]. The study proposed a multi-objective optimization framework to coordinate the energy consumption of home appliances based on dynamic pricing and load forecasting. The research findings highlighted the potential for IoT smart meters to enable real-time energy optimization and demand response, thereby contributing to effective demand-side management. A study was conducted on the design and implementation of cloud analytics-assisted smart power meters considering advanced artificial intelligence as edge analytics in demand-side management for smart homes [3]. The research emphasized the role of cloud-based analytics and advanced artificial intelligence in enabling smart power meters to facilitate demand-side management. Further elaboration was provided on the integration of IoT smart meters with cloud analytics and AI technologies [12].

Nepal, while still in the early stages of adopting smart grid technology has been making strides in implementing IoT in power systems. The country faces challenges such as a wide demand-supply gap and low accessibility to clean energy. Ongoing efforts aim to strengthen the power system, integrate renewable energy sources, and improve energy security. For instance, the Internet of Things in Nepal's power industry was explored, highlighting the potential for real-time monitoring and remote sensing. [5]

An overview of demand-response services was studied [13]. The study emphasized the role of demand-response programs in enabling consumers to actively participate in the management of electrical demand. The research findings underscored the potential for IoT smart meters to facilitate real-time communication and interaction between consumers and grid operators, thereby supporting the implementation of demand-response services for effective demand-side management. A study was conducted on the design, deployment, and performance evaluation of an IoT-based smart energy management system for demand-side management in smart grids [14]. The research focused on the integration of IoT smart meters to enable real-time monitoring, control, and optimization of energy consumption in smart grids. The findings highlighted the potential for IoT-based smart energy management systems to enhance the efficiency and reliability of demand-side management.

The literature highlights substantial advancements in IoT-based demand-side management (DSM) systems, including improvements in forecasting and optimization techniques for efficient energy management. However, significant knowledge gaps remain particularly in understanding the long-term impacts of these systems on electrical grids. While many studies emphasize the potential for IoT smart meters to provide real-time data and support adaptive demand forecasting, there is limited research exploring the practical integration of day-ahead pricing with real-time analytics and adaptive consumer models. Addressing these gaps is essential for further enhancing the efficiency and reliability of DSM in power systems.

Overall, the state of the art in IoT-based DSM showcases a dynamic evolution, driven by advancements in real-time monitoring, control mechanisms, and predictive analytics. Pioneering work by researchers like Marinescu et al. and Stephens et al. has demonstrated the role of IoT in capturing granular energy data, enabling game-theoretic models, and enhancing demand response programs.

More recent studies explore the integration of cloud and AI technologies, enhancing IoT systems for high-precision demand forecasting and price optimization [15, 16]. Collectively, these advancements lay a solid foundation for ongoing research and highlight the transformative role of IoT and data-driven techniques in next-generation energy management solutions.

The literature shows how IoT-based smart meters can significantly improve demand-side management by enabling accurate forecasting and real-time monitoring. While advancements in forecasting and optimization techniques are rapid, particularly through AI and cloud integration, there are still challenges, especially with integrating day-ahead pricing and real-time analytics. More research is needed to address these gaps and unlock the full potential of IoT in optimizing energy consumption and demand side management for future energy systems.

3. Methodology

The literature highlights methodologies emphasizing the integration of IoT-enabled smart meters for real-time data collection and the development of predictive algorithms to enhance demand-side management. Several studies focus on capturing granular energy consumption data to improve forecasting accuracy [1, 6]. Optimization techniques such as dynamic pricing models [8] and game-theoretic approaches [2] are key components in forecasting. Validation often involves comparing simulation results with real-world implementations evident in Nepal's energy grid advancements [5].

3.1. Initial Study

The study started from the selection of domain and explored into the following phases.

3.1.1. Domain Selection

Domain selection is a crucial step for commencing the study. The domain of this study has been selected as IoT and Energy Management.

3.1.2. Literature Review

A thorough literature survey was conducted to identify the gaps and see how similar systems were implemented as provided in the earlier Chapter 2. The literature review revealed significant advancements and persistent gaps on day-ahead price forecasting systems for electrical demand-side man-

agement and IoT smart meters.

3.1.3. Gap Analysis

Analysis of the gap in the domain was done by going through the available literature. A detailed identification is illustrated in the earlier section of Literature review. Literature review was done by studying the current practices done in the field of energy management research which associated the use of IoT in different aspects. The gap analysis identifies that little research has been done to analyze smart energy demand management and urgency of additional works in the sector.

3.1.4. Data Collection and Preprocessing

The data used for this research was originally published by [17] and is openly available via Mendeley Data. A mirrored version is also accessible through Kaggle [32]. The codebase and preprocessed data are available in the author's github repository [31].

3.2. Hardware and Connectivity Setup

3.2.1. Smart Meter System Design

The design of the smart meter system involved integrating the ESP32 microcontroller with essential sensors and components. The PZEM sensor was used for measuring electrical parameters, and the DS3231 real-time clock ensured precise timekeeping. A display module was incorporated to provide real-time feedback to users. The system was housed in a compact, durable casing to ensure reliability and ease of installation.

3.2.2. Communication Protocol Setup

The setup of communication protocols was critical for the seamless operation of the smart meter. The PZEM sensor communicated with the ESP32 via UART while the DS3231 RTC used the I2C protocol. These communication protocols were chosen for their reliability and efficiency in data transfer between the components and the microcontroller.

3.2.3. Interfacing with Peripherals

Interfacing the ESP32 with peripherals involved configuring the microcontroller to read data from the PZEM sensor and DS3231 RTC accurately. This process included writing firmware to handle data acquisition, ensuring that the readings from the sensors were correctly interpreted and processed by the ESP32.

3.2.4. Connection with Cloud

The ESP32's Wi-Fi capability was utilized to connect the smart meter system to the Firebase Realtime Database. This connection enabled the continuous upload of collected data to the cloud, ensuring that real-time information was availa-

ble for further processing and analysis. The system was configured to handle network connectivity issues gracefully, ensuring data integrity and reliability.

3.3. Data Analysis and Model Training

Different Machine learning algorithms and models were studied and explored based on the nature of data and literatures. The selected models and explained in below.

3.3.1. Long Short-Term Memory Network

Each Long Short-Term Memory (LSTM) cell is structured with three primary gates: the forget gate, input gate, and output gate. These gates regulate the flow of information into and out of the cell. Long Short-Term Memory networks are a specialized type of recurrent neural network (RNN) designed to handle time series data by capturing long term dependencies. During the training phase, the prepared data is fed into the LSTM model, which learns to predict future values based on historical observations. The LSTM's architecture, with its memory cells and gating mechanisms, allows it to retain information over extended periods, making it particularly suited for forecasting tasks where past patterns influence future outcomes [18-20].

3.3.2. CNN-LSTM Hybrid Mode

A CNN-LSTM hybrid model combines Convolutional Neural Networks (CNNs) and LSTM networks, utilizing the strengths of both architectures to handle complex data patterns, such as spatial-temporal data in video sequences, sensor data, or time-series data with spatial relationships [17]. The CNN-LSTM hybrid model leverages the strengths of both CNNs and LSTM networks. CNNs are effective at detecting local patterns in the data such as trends and seasonality by applying convolutional filters. These extracted features are then passed to an LSTM network to capture the temporal dependencies [21, 22].

3.3.3. GRU Model

Gated Recurrent Unit (GRU) is a type of recurrent neural network (RNN) architecture designed to handle sequence data while addressing issues like the vanishing gradient problem. GRUs, like Long Short-Term Memory (LSTM) network uses gates to manage information flow [23]. However, GRUs have a simpler structure with only two gates—the update gate and reset gate—making them computationally efficient and often effective for various sequence modeling tasks [24]. GRU networks are a variant of RNNs that simplify the LSTM architecture while retaining the ability to handle long-term dependencies. The GRU model is trained on the prepared data to forecast future values. GRUs use gating mechanisms to control the flow of information, which helps in learning temporal patterns effectively. They are computationally more effi-

cient than LSTMs as they offer faster training times while maintaining similar predictive performance, making them a practical choice for real-time forecasting [25].

4. System Design and Implementation

4.1. System Architecture

The smart meter system is designed to monitor and report real-time electricity consumption data. At the core of this system is an ESP8266 microcontroller, which manages data collection, processing, and communication tasks. The micro-

controller also features a built-in wireless network adaptor. PZEM sensor is connected to the microcontroller to measure key electrical parameters such as voltage, current, power, and overall energy consumption. This data is processed and displayed locally using an LCD display module.

The system integrates a DS3231 real-time clock module for time stamped data recording. The recorded data is stored on an REES52 SD card module. The microcontroller is also connected to the cloud and sends the Real Time data to the cloud. Specifically, the data is sent to a Firebase real-time database, where it is made accessible for further processing.

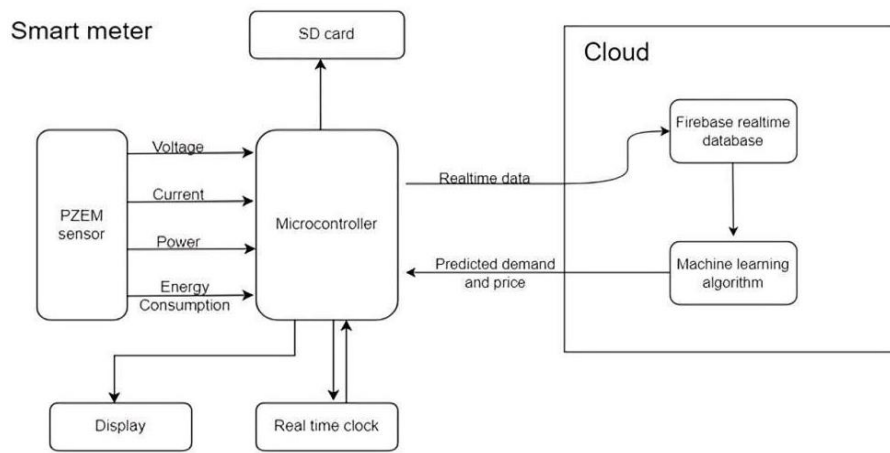


Figure 1. System Architecture of Smart Meter.

4.2. Hardware Components

4.2.1. ESP8266 Microcontroller

The ESP8266 microcontroller is the central component of the system. It features IEEE 802.11 b/g/n wireless network adapter with support for WPA and WPA2. The Wi-Fi module is specifically compatible with 2.4 GHz networks. The microcontroller also features SPI (Serial Peripheral Interface) and I2C (Inter-Integrated Circuit) communication protocols.

The SPI protocol is used for interfacing with the SD card module, and the I2C protocol facilitates communication with the DS3231 RTC module and LCD display.

4.2.2. PZEM-004T Sensor

PZEM 004T sensor PZEM-004T is a hardware device that functions to measure parameters of voltage, current, active power, and power consumption (kWh). It operates by directly interfacing with the electrical circuit. This data is communicated to the ESP8266 microcontroller via serial communication. The sensor outputs data in a structured format.

PZEM-004T Module parameter specification: i. Working voltage: 80 – 260 VAC ii. Test voltage: 80 - 260VAC iii. Rated power: 100 A/22000W iv. Operating frequency: 45 –

65 Hz v. Measurement accuracy: 1.0.

4.2.3. DS3231 RTC Module

The DS3231 real-time clock (RTC) module provides highly accurate timekeeping, crucial for timestamping data. It communicates with the ESP8266 microcontroller using the I2C protocol. Time values on the DS3231 can be set and reset through specific I2C commands sent from the microcontroller. The DS3231 is known for its accuracy, typically ± 2 ppm from 0 °C to +40 °C, which translates to an annual drift of less than a minute.

4.2.4. LCD Display Module

The system includes a 20 x 8 LCD display module, which communicates with the ESP8266 microcontroller using the I2C protocol. This display is used to show real-time electrical measurements and other relevant information to the user. The display's parameters, such as text position and visibility, are controlled through I2C commands of the microcontroller.

4.2.5. REES52 SD Card Module

The REES52 SD card module provides local storage for historical data logging, interfacing with the ESP8266 micro-

controller via the SPI protocol. This module allows for the recording of logged of data. The SPI protocol provides data transfer between the microcontroller and the SD card, for data logging operations.

4.3. Software Components

The software tools and components used in the research are elaborated below.

4.3.1. Microcontroller Programming

Platform IO was used as development environments for programming the ESP32.

Libraries used:

- i. Wire. h: For I2C communication with DS3231.
- ii. PZEM004T. h: For reading data from the PZEM-004T power sensor.
- iii. LiquidCrystal_I2C. h: To control the LCD via I2C.
- iv. SD. h: To read/write data on the SD card.

4.3.2. Data Processing and Machine Learning

The steps carried out during the research for data collection, pre-processing of data and selection and use of machine

learning models is shown in Figure 2.

4.3.3. Data Analysis

The study uses chronological data from Panama's electricity market including national electricity demand, temperature, humidity and wind velocity. The data spanned for multiple years and was indexed by datetime for time series analysis. A sample data table is shown in Figure 4.

Figure 3 shows the plot of demand from the year 2015 to 2020 in Megawatts hour (MWh). From the figure we can observe the minimum and maximum demand load from the year 2015 to 2020. The observation shows maximum demand in the year 2020 reaching above 1750 MWh and minimum demand in the year 2019 reaching below 250 MWh.

4.3.4. Sine and Cosine Transformations

Feature engineering is crucial for enhancing the predictive power of machine learning models. Temporal features such as day of the year, month, day of the month, day of the week, and hour of the day were created. Sine and cosine transformations was used to capture daily and yearly seasonal patterns.

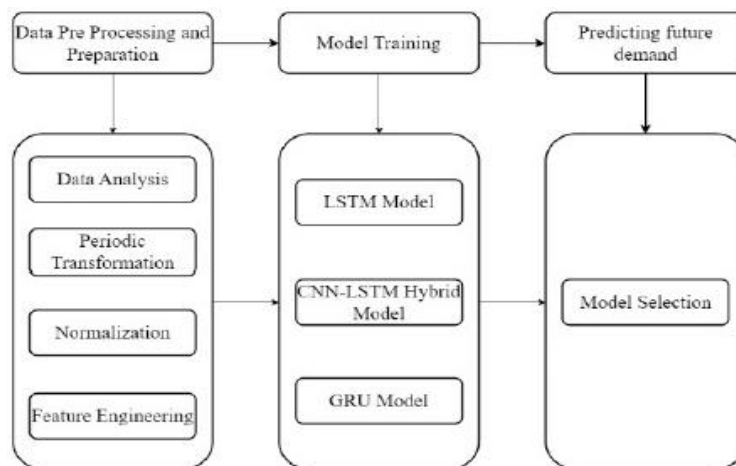


Figure 2. Data processing and machine learning process.

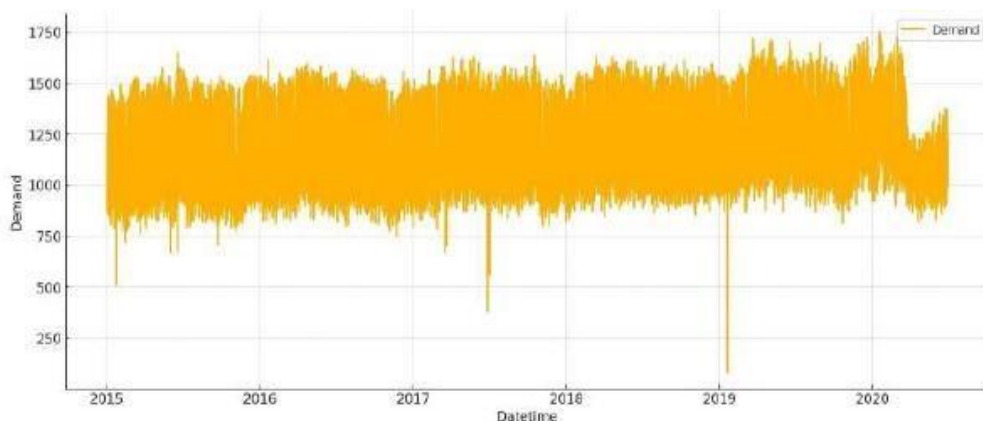


Figure 3. Plot of demand from 2015 to 2020.

	demand	day_of_year	month	day_of_month	day_of_week	hour_of_day	temp	hum	wind_vel	holiday	day_sin	day_cos	year_sin	year_cos
datetime														
2015-01-03 01:00:00	970.3450	3	1	3	5	1	25.865259	0.018576	21.850546	1	0.258819	9.659258e-01	0.036619	0.999329
2015-01-03 02:00:00	912.1755	3	1	3	5	2	25.899255	0.018653	22.166944	1	0.500000	8.660254e-01	0.037336	0.999303
2015-01-03 03:00:00	900.2688	3	1	3	5	3	25.937280	0.018768	22.454911	1	0.707107	7.071068e-01	0.038052	0.999276
2015-01-03 04:00:00	889.9538	3	1	3	5	4	25.957544	0.018890	22.110481	1	0.866025	5.000000e-01	0.038768	0.999248
2015-01-03 05:00:00	893.6865	3	1	3	5	5	25.973840	0.018981	21.186089	1	0.965926	2.588190e-01	0.039484	0.999220
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2018-12-31 04:00:00	948.5128	365	12	31	0	4	24.876184	0.017292	21.425257	0	0.866025	5.000000e-01	-0.012314	0.999924
2018-12-31 05:00:00	969.7473	365	12	31	0	5	24.936121	0.017346	20.305739	0	0.965926	2.588190e-01	-0.011597	0.999933
2018-12-31 06:00:00	953.2975	365	12	31	0	6	24.965051	0.017398	19.125606	0	1.000000	1.189198e-11	-0.010881	0.999941
2018-12-31 07:00:00	1018.9253	365	12	31	0	7	25.819055	0.017610	21.044226	0	0.965926	-2.588190e-01	-0.010164	0.999948
2018-12-31 08:00:00	1131.7573	365	12	31	0	8	26.985040	0.017344	24.822141	0	0.866025	-5.000000e-01	-0.009447	0.999955

Figure 4. Sample of dataset used for training.

4.3.5. Data Splitting and Preprocessing

The dataset was split into training, validation, and test sets to evaluate model performance on unseen data. Input features were normalized using the mean and standard deviation of the training data to ensure uniformity and improve model performance.

4.4. Model Training

The development of the models for forecasting involved preprocessing, creation of temporal features and division into training and testing sets. First, the data was preprocessed to obtain temporal features such as hour of the day, day of the week, and seasonal components using sine and cosine transformations. The dataset was then split into training, validation, and test sets. Each model's architecture was defined: the LSTM model utilized memory cells and gating mechanisms to capture long-term dependencies, the CNN-LSTM hybrid model combined convolutional layers to detect local patterns with LSTM layers to capture temporal dependencies, and the GRU model employed gating mechanisms for efficient training and effective learning of temporal patterns. Hyperparameter tuning was performed using Keras Tuner to optimize configurations such as the number of units, dropout rate, and learning rate for each model [26]. The models were trained on the historical data, and their performance was evaluated using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) metrics [27].

4.3.1. LSTM Model

The graph in Figure 5 shows the actual demand and prediction forecast of demand in Megawatts hour using the LSTM Model.

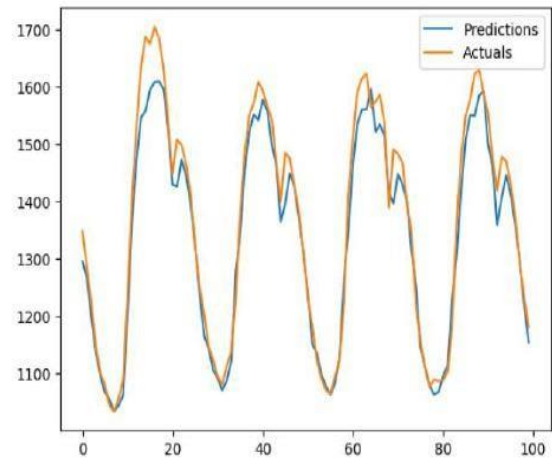


Figure 5. Prediction plot of LSTM model.

4.3.2. CNN-LSTM Hybrid Model

The graph in Figure 6 shows the actual demand and prediction forecast of demand in Megawatts hour using CNN-LSTM hybrid model.

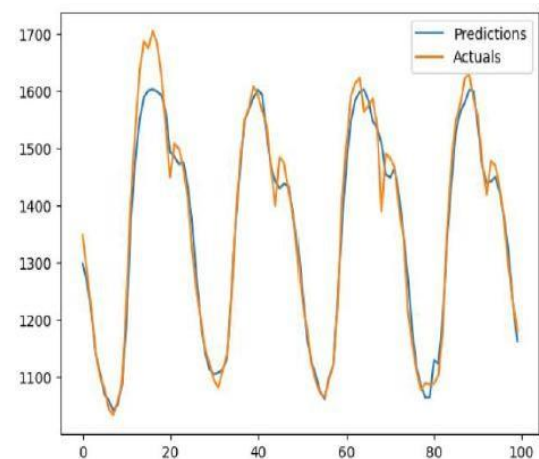


Figure 6. Prediction of CNN-LSTM hybrid model.

4.3.3. GRU Model

The graph in Figure 7 shows the actual demand and prediction forecast of demand in Megawatts hour Gated Recurrent Unit (GRU) Model.

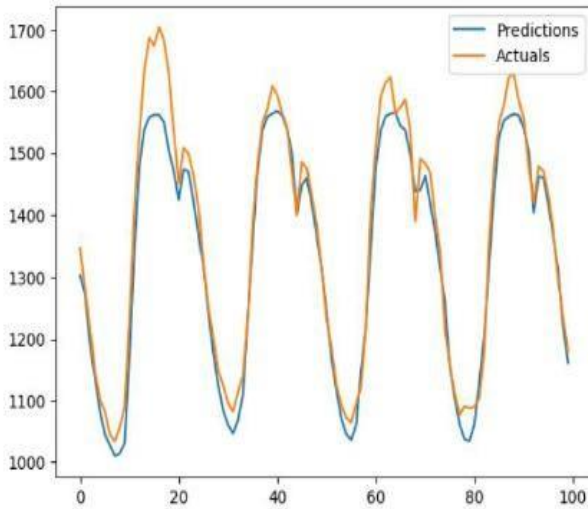


Figure 7. Prediction plot of GRU model.

5. Results and Evaluation

Model Selection

The performance of the models was evaluated using Root Mean Squared Error (RMSE), a common regression metric. The evaluation process involved splitting the dataset into training, validation, and test sets, followed by training the models (LSTM, CNN-LSTM, and GRU) on the historical electricity demand data. Hyperparameter tuning was performed using Keras Tuner to find the best configurations for each model. Predictions were then made on the test set, and the RMSE values were calculated to measure the accuracy of the models' predictions. Lower RMSE values indicate better model performance, meaning the model's predictions are closer to the actual values. The comparative analysis of these metrics across different models allowed us to determine which model performed best for day-ahead electricity load forecasting. Additionally, visualizing the predictions against the actual values provided further insights into the predictive capabilities of each model.

The LSTM model demonstrated strong performance in capturing the temporal dependencies in the electricity demand data. The loss plot of LSTM model for train loss vs validation loss is shown in Figure 8.

The loss plot of CNN-LSTM hybrid model for train loss vs validation loss is shown in Figure 9.

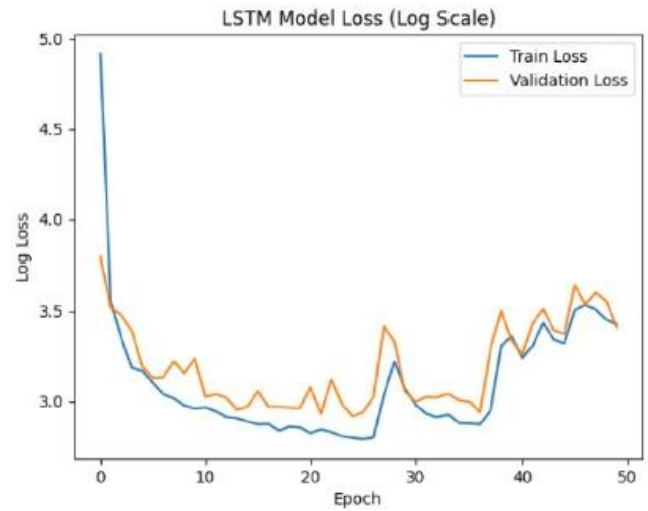


Figure 8. LSTM model loss plot.

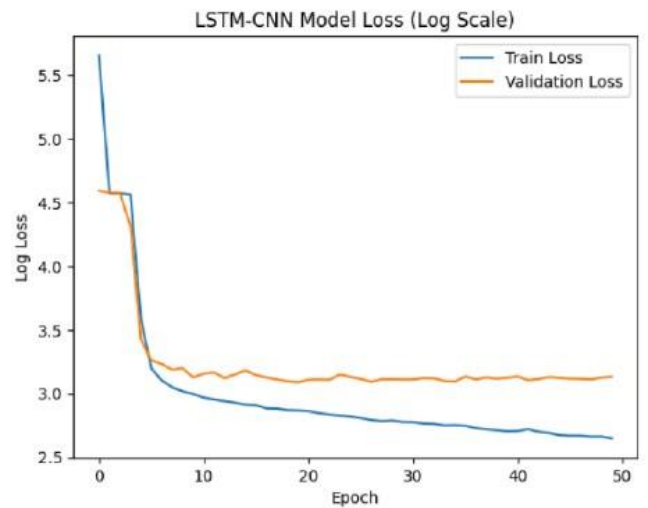


Figure 9. CNN-LSTM model loss plot.

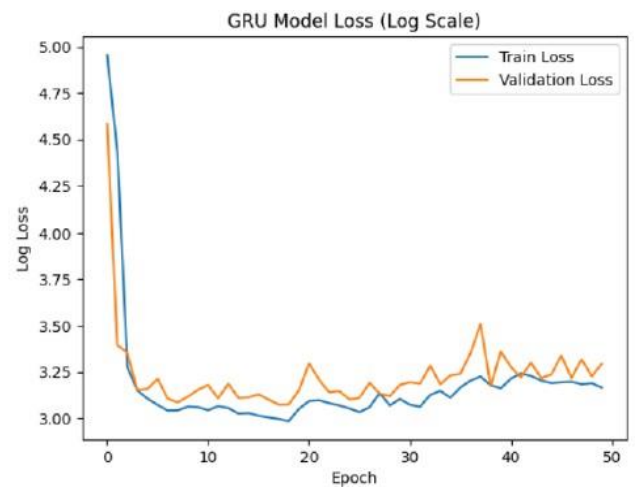


Figure 10. GRU model loss plot.

The loss plot of GRU model for train loss vs validation

loss is shown below in Figure 10.

The comparative analysis of the LSTM, CNN-LSTM, and GRU models in Figure 11 reveals that while all three models are capable of fairly accurate forecasting, the LSTM model (with RMSE = 31.6) consistently achieved the lowest RMSE value. Therefore, the LSTM model was used in deployment. The analysis indicated that the Long Short-Term Memory (LSTM) model was the most effective in forecasting electricity demand as it performed the CNN-LSTM hybrid (RMSE=33.2) and Gated Recurrent Unit (GRU) models (RMSE=37.1). The LSTM model's superiority in capturing temporal dependencies within the electricity demand data was evident through its consistently lower Root Mean Squared Error (RMSE) values. This highlights its robustness in dealing with the dynamics of electricity usage patterns, making it an indispensable tool in predictive analytics for energy management. As all three models were designed to handle sequential data - for this study the LSTM model performed best as demonstrated from least RMSE values.

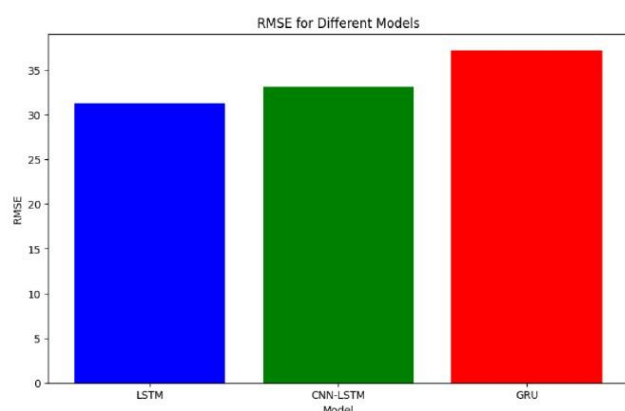


Figure 11. RMSE for different models.

6. Conclusion and Future Works

6.1. Conclusion

The integration of smart meters with IoT has proven to be a cornerstone in advancing demand forecasting accuracy and operational efficiency in energy management. The LSTM model emerged as a particularly effective tool, offering superior predictive accuracy that can significantly influence energy pricing and consumption behaviors.

This study underscores the critical role of advanced predictive models and real-time data analytics in shaping future energy systems. Smart meters and IoT extend beyond mere technological upgrades as they enhance demand forecasting and enable dynamic pricing. These technologies are pivotal to the evolution of smart grids and sustainable energy management.

This study recommends continued investment in the development of sophisticated predictive models and IoT infra-

structure. Similarly, regulatory frameworks should evolve to support technological innovations in energy management, ensuring data security and privacy while fostering market competitiveness. Further research into the integration of renewable energy sources with smart grid technologies could offer breakthroughs in achieving a balanced and resilient energy ecosystem.

6.2. Future Work

This study recommends incorporating more historical load data, especially for unique situations like holidays, can improve model accuracy. A promising development would be creation of dedicated model for holiday forecasts and combining its predictions with those of a general model for regular days. Using stacking techniques to merge these forecasts could further enhance accuracy, although this would likely increase both training and prediction times [28].

The research illuminated numerous benefits, notably the enhancement of energy consumption efficiency and grid stability [29]. Smart meters and IoT technologies empower utilities to finely tune demand management, reducing the necessity for costly infrastructure expansions and minimizing energy waste. However, challenges such as complex integration of diverse technologies such as smart meters, IoT devices, and sophisticated forecasting models were prevalent while conducting the study.

Ensuring accurate and secure real-time data flow among these components presents as formidable challenge requiring meticulous attention to system design and security protocols. The integration of smart meters and IoT technologies promises substantial impacts on the electricity market by refining demand forecasting and facilitating responsive pricing strategies. By harnessing more accurate predictions of electricity demand, dynamic pricing models can be implemented more effectively. These models encourage consumption during off-peak hours, optimizing grid stability and efficiency. Such advancements are likely to drive regulatory changes that promote the use of real-time data, fostering a competitive and sustainable energy market landscape.

Future research could explore the development of advanced machine learning models that more adeptly handle variability in energy consumption patterns [30]. Additionally, integrating renewable energy sources into the grid, facilitated by smart meters and IoT, could significantly enhance the predictability and management of power generation fluctuations. This could pave the way for more sustainable and resilient energy systems.

Abbreviations

IoT	Internet of Things
DSM	Demand-Side Management
ESP	Microcontroller models (Espressif Systems)
RTC	Real-Time Clock
PZEM	Power Meter Sensor (e.g., PZEM-004T)

SD	Secure Digital (Card Module)
LCD	Liquid Crystal Display
UART	Universal Asynchronous Receiver-Transmitter
I2C	Inter-Integrated Circuit
SPI	Serial Peripheral Interface
LSTM	Long Short-Term Memory
CNN	Convolutional Neural Network
GRU	Gated Recurrent Unit
RNN	Recurrent Neural Network
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
AI	Artificial Intelligence

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Data Availability Statement

The dataset used in this study is publicly available at Mendeley Data [17].

Conflicts of Interest

The authors declare no conflicts of interest.

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