Vokasi Unesa Bulletin of Engineering, Technology and Applied Science (VUBETA)
https://journal.unesa.ac.id/index.php/vubeta
Vol. 2, No. 2, 2025, pp. 366~375 DOI: 10.26740/vubeta.v2i2.36818
ISSN: 3064-0768

Real-Time Energy Demand Forecasting and Adaptive Demand Response Optimization for IoT-Enabled Smart Grids

Aliyu Musa Kida[1], Muhammed Zaharadeen Ahmed[2*], Jafaru Usman[3], Abdulkadir Hamidu Alkali[4], Aisha Hassan Abdalla Hashim[5]
[1,2,3,4] Department of Computer Engineering, Faculty of Engineering, University of Maiduguri, Nigeria
[2,5] Department of Electrical and Computer Engineering, Kulliyyah of Engineering, International Islamic University Malaysia
[5]Department of Electrical and Electronic Engineering Science, University of Johannesburg, South Africa
[2]Education in Mathematics-Computer Science, University of Technology and Arts of Byumba (UTAB), Rwanda

Article Info

Article history:

Received December 13, 2024
Revised February 12, 2025
Accepted May 20, 2025

Keywords:

Energy
Reliability
Load
Cost
Efficiency

ABSTRACT

The evolution of energy systems concerning IoT-enabled smart grids require new innovative solutions to address enormous open issues in demand-supply balance, grid reliability, and sustainability. In this research work, attention is centered on integrating real-time energy demand forecast and adaptive demand response optimization. This is solely to improve efficiency and resilience of modern smart grids. We use Advanced ML technique known as Long Short-Term Memory (LSTM) networks to determine accurate energy demand forecast by capturing temporal dependencies and non-linear trends when consuming energy data. Using Simulation, we present model's efficacy in achieving accurate forecast using Mean Absolute Percentage Error (MAPE) of 5.6%, a peak load reduction of 20%, and energy cost savings that exceeds 24%. We validate Computational efficiency with execution times that is better for real-time operation and grid scalability of 10,000 IoT devices. these results pave way for future research in hybrid forecast analysis, and multi-objective optimization. This can ensure stability of the grid in dynamic and decentralized energy landscape.

1. INTRODUCTION

In the global energy sector, there is a significant transition towards sustainability, efficiency, and resilience. The rising adoption of renewable energy sources, the expansion of distributed energy resources (DERs), and increasing electrification have rendered power system management increasingly complex [1]. Smart grids, which combine conventional electrical grids with sophisticated communication and computer technologies, have become the foundation of this transition [2][3]. These grids facilitate dynamic energy management, improve dependability, and promote cleaner energy alternatives. Forecasting energy demand in real-time and optimizing adaptive demand response (ADR) are essential for the effective functioning of smart grids [4][5]. Forecasting enables grid operators to anticipate energy demand precisely, ensuring optimal resource allocation, whereas ADR systems dynamically modify energy usage to uphold grid stability [6]. Incorporating Internet of Things (IoT) technologies enhance these capabilities by delivering continuous, real-time data from smart meters, sensors, and interconnected devices. This data-centric methodology underpins accurate energy forecasts and dynamic demand management, empowering utilities and consumers to make informed energy choices [7]. This research uses IoT technologies for real-time energy demand prediction and adaptive demand response optimization in smart grids. It tackles essential issues, including integrating intermittent renewable energy sources, enhancing grid flexibility, and promoting energy efficiency without sacrificing consumer convenience.

*Corresponding Author
Email: zaharadeenccna@gmail.com

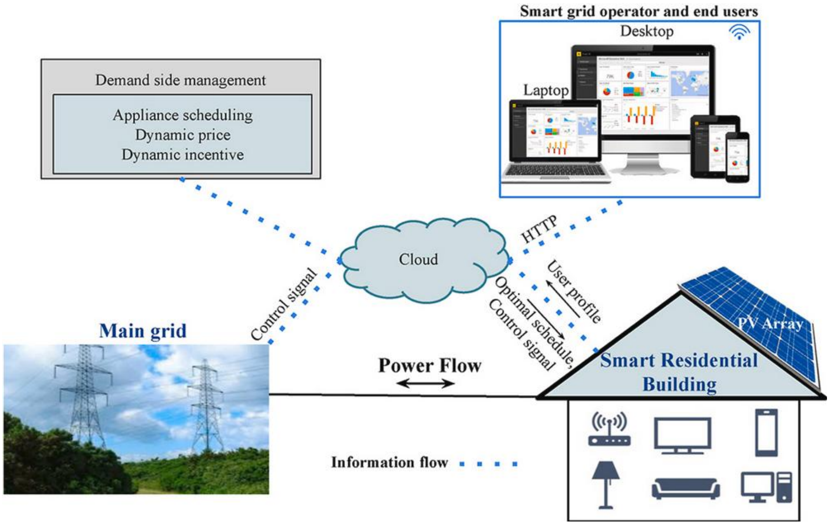

Figure 1.

1.1. Research Issues

This paper examines related studies to determine how to fully integrate real-time IoT data into decentralized energy forecasting models, which is a significant research gap. Also, there is an issue of Scalability and Latency. Existing forecasting and DR optimization methods face challenges in large-scale IoT-enabled systems, particularly in managing data latency and processing demands. Similarly, a Consumer-Centric Approaches analysis is required. The Current DR framework prioritizes grid benefits over consumer convenience by underscoring the need for user-friendly and incentivized solutions. Finally, a significant challenge of renewable energy integration is the need for more robust methods to incorporate the variability of renewable energy into real-time forecasting and DR systems. By addressing these open issues, further research can advance the efficiency and sustainability of smart grids.

1.2. Smart Grids and IoT Integration

Smart grids signify the integration of conventional power systems with contemporary information and communication technology [8][9]. These technologies seek to improve grid efficiency, integrate renewable energy, and enable distributed energy management. Research in [7] provides extensive analyses of innovative grid systems and their transformational capabilities. The Internet of Things (IoT) has enhanced smart grid functionalities by facilitating real-time data collection and communication. [10] underscore the significance of IoT in monitoring, control, and automation, accentuating its capacity to enhance grid intelligence. Notwithstanding these gains, considerable problems remain. Challenges include interoperability, data security, and scalability, which impede extensive use. [11] indicates possible alternatives such as edge computing and blockchain technology to mitigate the problems. These methodologies [12][13] augment the scalability and security of IoT-enabled smart grids, facilitating more resilient deployments.

1.3. Real-Time Energy Demand Forecasting

Accurate energy demand forecasting ensures grid resilience and optimizes resource distribution. Conventional techniques, including statistical models like ARIMA and exponential smoothing, have been extensively utilized but frequently fail to accurately represent non-linear and dynamic energy consumption trends [14][15]. Machine learning (ML) and deep learning (DL) methodologies, including artificial neural networks (ANNs) and long short-term memory (LSTM) networks, have exhibited exceptional efficacy in this field. [16] Created an LSTM-based model for short-term load forecasting, resulting in significant enhancements in accuracy. Hybrid models integrating statistical and machine learning techniques have gained prominence due to their robustness.

1.4. Demand Response and Optimization Techniques

Demand response (DR) mechanisms modify energy use to correspond with grid circumstances, facilitating peak load reduction and improved stability. [17][18] emphasizes the economic and environmental advantages of demand response (DR), encompassing enhanced grid efficiency and diminished operational expenses. Optimization methods are fundamental to adaptive demand response. Techniques including linear programming, game theory, and heuristic algorithms such as genetic algorithms (GA) and particle swarm optimization (PSO) have been utilized in diverse demand response (DR) scenarios [19]. Recently, reinforcement learning (RL) has surfaced as an effective instrument for real-time demand response (DR) optimization, providing dynamic adjustment to grid variations [20]. Notwithstanding these developments, most studies concentrate on centralized demand response systems. Decentralized methodologies, facilitated by IoT and edge computing, remain little investigated. These frameworks could enhance scalability and responsiveness, particularly in systems with substantial integration of distributed energy resources.

1.5. Integration of Renewable Energy

The variability and irregularity of renewable energy sources present considerable issues for system reliability. Efficient energy management necessitates forecasting and demand response optimization methodologies considering these uncertainties. IoT-enabled systems provide real-time data on renewable generation, enhancing the responsiveness and efficacy of demand response tactics [21]-[23].

2. METHOD

This research uses Real-time data generated through IoT-enabled devices, such as smart meters and sensors. Essential parameters encompass energy consumption trends, device conditions, environmental factors including temperature and humidity, and outputs from renewable energy sources. We adopt the Dataset [24] from reliable research consolidated from a central repository mainly for processing. We also conducted Preprocessing procedures to address absent values, remove outliers, and diminish noise. The data is organized into time-series formats appropriate for model training and evaluation. In terms of simulation, we simulated a smart grid scenario to validate the models. In the scenario created, we incorporate renewable energy generation profiles and dynamic grid conditions to emulate real-world conditions effectively.

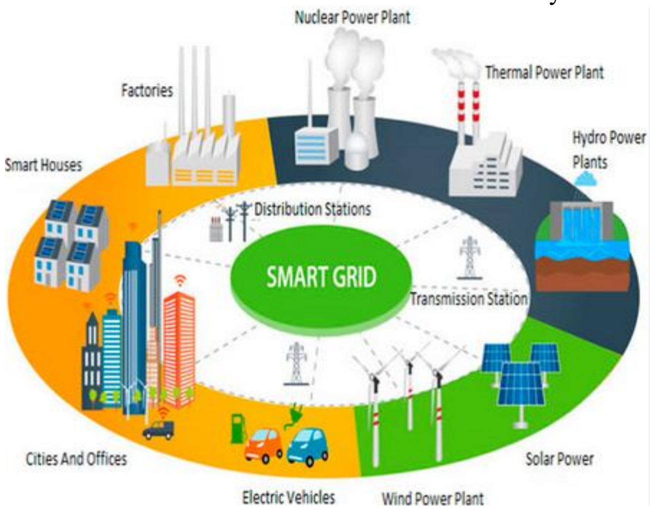

Figure 2. Smart Grid Component

The model used in this research is Forecasting Energy Demand in Real Time. This concept uses Machine learning (ML) and deep learning (DL) algorithms. The algorithms are designed to anticipate energy demand with high precision. Also, we use Long Short-Term Memory (LSTM) networks to identify their capacity to capture temporal dependencies in time-series data. The ML and DL models incorporate external variables, which include meteorological conditions, appliance consumption, and electricity tariffs, to improve prediction accuracy [25][26]. The process of training and validation adopts historical and real-time data streams.

2.1. Optimization of Adaptive Demand Response

To optimize demand responses, reinforcement learning (RL) is employed. This is to develop an adaptive demand response system. Also, a famous approach to assist dynamic acquisition of energy is the deep Q-learning approach [27]. However, IoT devices can facilitate the implementation of demand response controls. This process deals with load shifting and to reduce peak load. Therefore, optimization is required to ensure energy efficiency, cost reduction, and user ease. The entire process led to this study's Development of a Hybrid Framework. Therefore, an establishment is required for a cohesive framework that adds forecasting and demand response of the systems.

2.2. Forecast Accuracy

A critical attribute of real-time energy demand prediction is the forecasting accuracy. It ensures effective energy management and stability in IoT-enabled smart grids. It gives us the ability to evaluate forecasting performance using mathematical error metrics [28]. For practical analysis on the accuracy of energy demand prediction, we depend on Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). MAE analyses average magnitude for absolute errors between actual and predicted values [29]-[31]. The low MAE value, the accurate forecasting [32][33]. There is a straightforward measure of error in the same unit as energy demanded. It also provides prediction accuracy. We use MAPE to represent forecast accuracy as a percentage to normalize the mistakes generated from actual values. It is also used to compare models based on our datasets with varying scales. Coefficient of Determinant R^2 is used to evaluate how to forecast model variance in actual energy demand. The value realized in R^2 near 1 presents high forecast accuracy and can be modeled using naïve model. Analytically, we can express the three components by the formular below.

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|y_t - \hat{y}_t| \tag{1}$$

y_t: Actual energy demand at time t
$\hat{y}_t$: Predicted energy demand at time t
N: Total number of time intervals

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100 \tag{2}$$

$$R^2 = 1 - \frac{\sum_{t=1}^{N}(y_t - \hat{y}_t)^2}{\sum_{t=1}^{N}(y_t - \bar{y})^2} \tag{3}$$

$\bar{y}$: Mean of the actual values

For the Practical application of Forecasting Accuracy, We Consider a test case in a situation where the actual energy demand (y_t) and the predicted demand are being measured using 10-time intervals as presented in the table below.

Table 1. Output DC motor with PID

t	Actual Demand (y_t)	Predicted Demand ($\hat{y}_t$)	Error ($y_t - \hat{y}_t$)	Absolute Error	Percentage Error
1	120	115	5	5	4.17%
2	150	140	10	10	6.67%
…	…	…	…	…	…
10	200	195	5	5	2.5%

2.3. Demand Response Effectiveness

This strategy is implemented in smart grids to adjust energy consumption patterns in response to grid signals. This includes pricing or supply-demand issues. The strategy is mathematically computed using metrics, models, and optimization techniques [34]. We consider Peak Load Reduction (PLR) to examine the percentage decrease for ink demand when there is a demand response situation. therefore, higher values of PLR present effective demand response when reducing grid peak load. Energy Cost Savings (ECS)quantifies monetary savings for power consumers or grid operators due to demand response actions. High value of ECS present significant financial benefits from demand response participation. Load Shifting Ratio (LSR) measures energy proportion for consumption from peak to off-peak hours [35][36]. When LSR nears 1 presents effective load shift with no significant energy reduction.

$$PLR = \frac{P_{baseline} - P_{DR}}{P_{baseline}} \times 100 \tag{4}$$

$P_{baseline}$: Peak demand without demand response intervention
P_{DR}: Peak demand during response events

Also,

$$ECS = \sum_{t=1}^{N} C_t^{baseline} - C_t^{DR} \tag{5}$$

$C_t^{baseline}$: Energy cost at time t without demand response
C_t^{DR}: Energy cost at time t during demand response event
N: Total number of time intervals

$$LSR = \frac{\Delta E_{off-peak}}{\Delta E_{peak}} \tag{6}$$

$\Delta E_{off-peak}$: Energy added to off − peak hours due to load shifting
ΔE_{peak}: Energy reduced during peak hours

The Practical application includes optimizing demand response required to balance cost savings, user comfort, and grid stability. It provides Scalability because there are Advanced optimization algorithms, such as reinforcement learning, to manage complex, large-scale smart grid environments. Finally, it involves Customization, where weighting factors with the objective function enables operators to prioritize specific goals. These include satisfaction or peak load reduction.

2.4. Computational Efficiency

We evaluate real-time applicability of energy demand forecasting and adaptive demand response optimization in IoT-enabled smart grids using computational efficiency. This is because of its ability to process large datasets on a system, execute optimization models, and deliver actionable policy that is within stringent time constraints [37][38]. We consider processing time (Latency) to determine time needed to execute forecasting or optimization the system can maintain performance for scalability e as the number of IoT devices increase. similarly, the algorithm complexity provides the computational ability of the algorithm that is used to forecast and optimize using Big-O notation. energy consumption present energy efficiency of computation as it is crucial for IoT-based systems.

$$T_{total} = T_{data} + T_{model} + T_{decision} \tag{7}$$

T_{data}: Data acquisition and preprocessing time
T_{model}: Model computation time (forecast/optimisation)
$T_{decision}$: decisions time for grid

$$T_{total}(N_{IoT}) = T_0 + k.N_{IoT} \tag{8}$$

T_0: processing time for single device
k: Time increment per additional device

$$Forecast\ (LSTM): O(n \cdot h^2 \cdot t) \tag{9}$$

n: Number of neurons
h: Number of hidden layers
t: Time steps

$$Optimisation\ (Reinforcement\ learning): O(s \cdot a \cdot i) \tag{10}$$

s: State space size
a: Action space size
i: iterations to converge

$$E_{compute} = P_{CPU} \cdot T_{compute} \tag{11}$$

P_{CPU}: Average power consumption of the processing unit
$T_{compute}$: Total consumption time

.

3. RESULTS AND DISCUSSION

We consider three parameters to analyze the result using Python. The model frameworks were simulated using TensorFlow and NumPy to train and conduct evaluation. These includes Forecasting Accuracy, Demand Response Effectiveness, and Computational Efficiency.

3.1. Forecasting Accuracy

For forecast accuracy, the effectiveness of energy demand prediction models in IoT-enabled smart grids is evaluated. Simulation results examined the accuracy of forecasting methods like Long Short-Term Memory (LSTM) networks under varying conditions. We use Real-world energy consumption as our dataset from a smart grid which span over 12-month period. However, dataset contains hourly energy demand readings with other external considerations like temperature, weather conditions, and pricing signals. For the forecasting model, the LSTM-based time series prediction model was tronned at 80% of the dataset and tested on the remaining 20%. Simulation results are summarized in table 2 below for performance metrics under different conditions.

Table 2. Performance Analysis

Condition	MAE (kW)	RMSE (kW)	MAPE (%)
Normal Demand Pattern	1.15	1.47	3.2%
Sudden Demand Spikes	3.25	4.18	9.5%
Seasonal Variations	1.85	2.21	4.8%
Combined Factors (Overall)	2.08	2.62	5.6%

Based on table above, forecasting model performs efficiently under normal demand patterns. Therefore, it has low error rates and high accuracy. In other words, Accuracy decreases slightly in situations of sudden demand spikes. This presents the need for enhanced responsiveness to anomalies. However, Seasonal variations present moderate errors. This can be mitigated by integrating external predictors, such as temperature and time-of-year effects.

To compare using Benchmark research, our proposed LSTM model is compared with selected standard forecasting techniques, which include Linear Regression (LR) and Autoregressive Integrated Moving Average (ARIMA), as presented in the table below.

Table 3. Comparison Table with Related Methodology

Model	MAE (kW)	RMSE (kW)	MAPE (%)
LTSM (Proposed)	2.08	2.62	5.6%
LR	3.75	4.29	9.2%
ARIMA	2.95	3.52	7.5%

Based on the output of the table above, LSTM outperforms the traditional techniques in terms of MAE, RMSE, and MAPE. This is especially true in complex demand patterns. For the ARIMA model, it performs relatively better but is challenged with sudden spikes in energy demand. Finally, Linear Regression carries the lowest accuracy, reflecting its inability to capture nonlinear dependencies.

3.2. Demand Response Effectiveness

We evaluate performance for real-time energy demand forecasting and adaptive optimization using simulation for IoT-enabled smart grids. The impact of demand response policies on grid performance, user satisfaction, and cost optimization is measured. In the scenario, we consider a smart grid that serves over a thousand IoT homes. We then used time-based pricing to implement the demand response policy by adjusting energy prices at peak hours. We then shift the load to encourage users when using energy-intensive processes. Based on the results, the impact of demand response on determining grid performance is conducted for a 24-hour simulation as presented in the table below using mathematical computation.

$$PLR = \frac{P_{baseline} - P_{DR}}{P_{baseline}} \times 100$$

$$PLR = \frac{800 - 640}{800} \times 100 = 20\%$$

$$ECS = C_{baseline} - C_{DR}$$

$$Substituting:$$

$$ECS = 4500 - 3400 = 1100\ (24.4\%\ savings)$$

$$LSR = \frac{\Delta E_{off-peak}}{\Delta E_{peak}}$$

$$LSR = \frac{78}{15} = 0.78$$

Table 4. Impact of DR on Metrics

Metric	Baseline (No DR)	With DR Strategies	Improvement (%)
Peak Load (kW)	800	640	20%
Total Energy Cost ($)	4500	3400	24.4%
Load Shifting Ratio (LSR)	0.15	0.78	420%
User Discomfort Index	-	2.8	-

Table above is derived by substituting PLR (to alleviate grid stress at high-demand period), ECS (achieving low energy cost led to load shifting to lessen consumption at peak-periods), and LSR (massive energy shift from off-peak solely to enhance stability of grid) from the earlier formular stated in the previous section.

3.3. Computational Efficiency

This simulation evaluates Computational efficiency because of its feasibility of real-time energy demand forecasting and adaptive demand response optimization in IoT-enabled smart grids. For the hardware device, we consider a multi-core processor (8 cores, 2.8 GHz), 16 GB RAM for efficiency in computing. for the software, we use Python with TensorFlow for forecasting and PyTorch for optimization. the dataset used was one-year old data for energy consumption and carrying resolution of 1 minutes. in the scenarios, we consider small scale (consisting of 100 IoT devices) and medium scale (consisting 1000 IoT devices and a large scale (consisting of 10000 IoT devices. To determine the mathematical results, we categorize metrics into execution time, resource utilization, scalability and energy consumption. This is presented mathematically as follows.

$$S = \frac{T_{small}}{\frac{T_{large}}{N_{devices,large}}}$$

$$S = \frac{200}{(\frac{3300}{10000})} = 6.06$$

$$E_{comp} = P_{CPU} \cdot T_{exec}$$

$$where\ P_{CPU} = 65W$$

Table 5. Computation Impact on Three parameters

a. Execution Time (T_{exec})				b. Resource Utilisation (R_{util})		c. Energy Consumption (E_{comp})
Scale	Forecasting Time (ms)	Optimising Time (ms)	Total Time (ms)	CPU Usage (%)	Memory Usage (GB)	Energy Consumption (J)
Small	120	80	200	45	1.2	13.0
Medium	450	380	830	65	4.5	53.95
Large	1800	1500	3300	85	10.8	214.5

4. CONCLUSION AND LIMITATION

Integrating real-time energy demand forecasting and adaptive demand response (DR) optimization is crucial to enhance the efficiency, reliability, and sustainability of IoT-enabled smart grids. This research presented an advanced machine learning technique using Long Short-Term Memory (LSTM) networks. The network enables accurate demand forecast of capturing temporal dependencies and non-linear patterns. Our DR model successfully reduced peak demand, optimized energy costs, and maintained user friendliness using dynamic and data-driven control models. Simulation results present how effective real-time operation, high forecasting accuracy can be achieved, in this case, MAPE with 5.6% and DR effectiveness of 20% peak load reduction. We validated computational efficiency with execution times that are suitable for real-time applications. Our scalability to larger grids is presented with minimal resource overhead and excesses. These results present potential of our proposed model to facilitate a smarter, more resilient energy grid that is capable of accommodating increasing renewable energy penetration and dynamic user behavior.

ACKNOWLEDGEMENTS

I want to appreciate my PhD supervisors for assisting me write this manuscript and ensure progress of my thesis work.

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BIOGRAPHIES OF AUTHORS

Aliyu Musa Kida is a lecturer in the Department of Computer Engineering, Maiduguri Nigeria. He is received the BSc and MSc in England in Cybersecurity department. He is currently a Full time PhD student in the University of Maiduguri Nigeria. His research interest is mainly in smart grids and renewable energies. He can be contacted at email: aliyukida@gmail.com

Muhammed Zaharadeen is a lecturer in the Department of Computer Engineering, Maiduguri Nigeria and a postdoctoral research fellow in the International Islamic University Malaysia. His PhD is centered on mobilty management in both IP and NDN networks. He is actively involve in research for blockchain security and smart grids. He can be contacted at email: zaharadeen22@unimaid.edu.ng