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AR-IOT ENABLED REAL-TIME MONITORING AND PREDICTION OF ENERGY CONSUMPTION IN BUILDINGS

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Abstract

The growing global demand for electrical energy requires efficient monitoring and management solutions to op- timize usage and ensure sustainability. This paper proposes an IoT-based augmented reality (AR) real-time energy monitoring system designed to track and analyze and predict electricity consumption in buildings. The system monitors key electrical parameters such as voltage, current, active power, and power factor fluctuations, enabling users to make informed decisions to optimize energy consumption and reduce waste. The sys- tem architecture integrates IoT devices including NodeMCU microcontrollers and current sensors to collect real-time data. The data is transmitted to a cloud server for forecasting the consumption using Improved AutoRegressive Integrated Moving Average (IARIMA) and deep learning algorithms. This enables dynamic adjustments by predicting energy usage patterns, identi- fying inefficiencies, and providing actionable insights to optimize demand and supply. AR is integrated as a user-friendly feature that enables real-time visualization of energy consumption data through an interactive interface, thereby improving user accessi- bility and engagement. This work emphasizes the integration of IoT, AI, and AR to address challenges such as energy theft, billing inaccuracies, and time-based rate optimization. The system's ability to provide real-time feedback and actionable recommen- dations demonstrates its potential to significantly improve energy efficiency and

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sustainability in modern buildings. The results suggest that this approach could serve as a transformative energy management solution to meet the growing energy demands of the future.

***Index Terms*—component, formatting, style, styling, insert**

I. INTRODUCTION

The rising global energy demand, driven by rapid ur- banization and increased dependence on electrical devices, necessitates effective energy management solutions to ensure sustainability and mitigate resource wastage. Energy monitor- ing, which involves the systematic tracking and analysis of

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electricity consumption patterns, has emerged as a vital ap- proach for optimizing energy usage, forecasting future needs, and reducing operational inefficiencies [3]. In this context, the integration of advanced technologies such as IoT (Internet of Things), AI (Artificial Intelligence), and AR (Augmented Reality) offers promising advancements in real-time energy monitoring and management [7]. This paper focuses on the development of an innovative IoT-enabled energy monitoring system designed specifically for residential and individual accommodations to enhance energy efficiency and user en- gagement.

IoT is a transformative technology that connects physical devices, sensors, and systems to the internet, enabling real- time data acquisition, transmission, and processing [8]. In the proposed system, IoT facilitates the collection of energy consumption data using inductive clamps to measure current loads in electrical circuits. These measurements enable the identification of usage patterns for individual appliances and the detection of intermittent loads through a processor-driven analytical approach.

AI, a technology that mimics human cognitive functions such as learning, reasoning, and decision-making, plays a piv- otal role in this system. By employing advanced AI algorithms and deep learning techniques [20], the system analyzes energy consumption data to identify trends, predict demand, and optimize energy efficiency dynamically. Efficient Hybrid-AI based frameworks shall be effectively used for the prediction of electricity usage in buildings [14].

To enhance the accessibility and interoperability of energy data, the system incorporates AR technology [18], which overlays real-time digital information onto the physical en- vironment. This feature allows users to visualize their energy consumption intuitively through a three-dimensional interface,making complex data easier to understand and actionable. The architecture of the proposed system includes an infor- mation acquisition device for real-time monitoring, a cloud- based server for data storage and statistical analysis, and a user-friendly AR-based visualization platform. The system also addresses critical issues such as energy theft, inaccurate billing, and time-based tariffs, providing timely notifications and feedback to users.

This paper demonstrates how the integration of IoT, AI, and AR technologies in energy monitoring

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systems can signif- icantly enhance efficiency, sustainability, and user experience. The proposed approach not only contributes to effective energy management but also supports broader goals of sustainability and resource optimization by leveraging cutting-edge tech- nologies to meet modern energy challenges.

TABLE I ABBREVIATION

3D	Three-Dimensional
AC	Air Conditioner
ADC	Analog-to-Digital Converter
AR	Autoregressive Polynomial
ARE	Average Relative Error
CNN	Convolutional Neural Network
DLCA	Deep Learning-based Classification Algorithm
DNN	Deep Neural Network
ESP	Espressif Systems Processor
HTTP	HyperText Transfer Protocol
I/O	Input/Output
I2C	Inter-Integrated Circuit
IARIMA	Improved AutoRegressive Integrated Moving Average
ICA	Independent Component Analysis
ID	Identifier
IDE	Integrated Development Environment
MA	Moving Average Polynomial
MAE	Mean Absolute Error
MCU	Microcontroller Unit
MQTT	Message Queuing Telemetry Transport
PF	Power Factor
PWM	Pulse Width Modulation

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RMSE	Root Mean Square Error
RTC	Real-Time Clock
SDK	Software Development Kit
SPI	Serial Peripheral Interface
SRAM	Static Random-Access Memory
SSL	Secure Sockets Layer
TCP/IP	Transmission Control Protocol / Internet Protocol
TLS	Transport Layer Security
UART	Universal Asynchronous Receiver-Transmitter
UI	User Interface
V-I	Voltage-Current
Wi-Fi	Wireless Fidelity

II. RELATED WORKS

The integration of IoT and AI technologies for energy management in smart buildings and microgrids has been extensively studied in recent years. This section synthesizes insights from multiple papers to highlight the advancements, challenges, and future directions in this domain.

IoT-Based Energy Management Systems Several studies have proposed IoT-based systems for energy monitoring and optimization in smart buildings. [11] introduced a Build- ing Energy Management (BEM) IoT system that combines physics-based and learning-based methods to achieve nearly zero-energy goals. Similarly, [15] developed an IoT-based energy monitoring system for controlling lights and outlets in buildings, leveraging NodeMCU and Raspberry Pi for real- time data collection. [2] proposed Homergy, an IoT-based sys- tem for integrating non-smart appliances into energy-efficient ecosystems, demonstrating measurable energy savings in vari- ous consumer scenarios. These studies collectively emphasize the importance of IoT in enabling real-time monitoring, con- trol, and optimization of energy consumption in buildings.

Hybrid Approaches for Energy Optimization Hybrid ap- proaches combining physics-based and data-driven methods have gained traction for energy management. [11] employed reinforcement learning (RL) strategies for optimal scheduling of home appliances, while [27] introduced a Markov-chain- based model and the PF-PEC algorithm for proactive energy conservation in smart homes. [19] proposed a hybrid algorithm combining Regression Tree and Poly-Exponential models for efficient

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energy consumption forecasting. These studies highlight the effectiveness of hybrid methods in addressing the complexities of energy management, such as nonlinear building thermal dynamics and uncertain user behavior.

AI-Driven Predictive Analytics AI and machine learning (ML) techniques have been widely adopted for energy con- sumption prediction and optimization. [6] developed an Elman RNN model and an exponential model for predicting electric energy consumption in IoT-driven buildings. [26] proposed a Hidden Markov Model (HMM) for energy consumption prediction in residential buildings, outperforming traditional methods like SVM and ANN. [12] introduced a hybrid ARIMA-SVR model for electricity consumption forecasting, demonstrating superior accuracy for short-term predictions. These studies underscore the potential of AI-driven predictive analytics in enhancing energy efficiency and reducing opera- tional costs.

Challenges and Future Directions Despite significant ad- vancements, several challenges remain in the implementa- tion of IoT and AI-based energy management systems. [11] identified challenges such as integrating large-scale connected buildings and intelligent EV charging, while [22] highlighted scalability, cost, and data security issues in IoE-based systems.

[17] discussed data privacy, interoperability, and the need for skilled personnel as key barriers to the adoption of AI-driven systems. Future research directions include scaling systems to nearly zero-energy cities ([11]), integrating advanced control strategies ([22]), and exploring hybrid and deep learning models ([19], [12]).

Integration of Renewable Energy Sources The integration of renewable energy sources into energy management systems has been a focal point of recent research. [22] emphasized the role of IoT-based solar monitoring systems in optimizing solar energy generation and maintenance. [4] discussed the integration of energy storage systems (ESSs) and intelligent charging methods for electric vehicles in smart cities. These

studies highlight the importance of renewable energy integra- tion in achieving sustainability goals and reducing reliance on traditional energy sources.

Real-World Applications and Case Studies Several studies have validated their proposed systems through real-world applications and case studies. [11] demonstrated the perfor- mance of their BEM IoT system in connected buildings, achieving significant reductions in energy consumption. [15] tested their IoT-based energy monitoring system in the Mabini Building, showing measurable energy savings. [27] validated the PF-PEC algorithm in real-world smart home environments, achieving up to 36

III. PROPOSED METHODOLOGY

A system platform based on the IoT technology was devel- oped to enable building energy consumption monitoring along- side prediction and visualization functions. The methodology comprises Sensor Unit and Edge Processing (NodeMCU) and Cloud Server and User Interface as its four major components.

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The system workflow is shown in Figure 1 in the block diagram presentation.

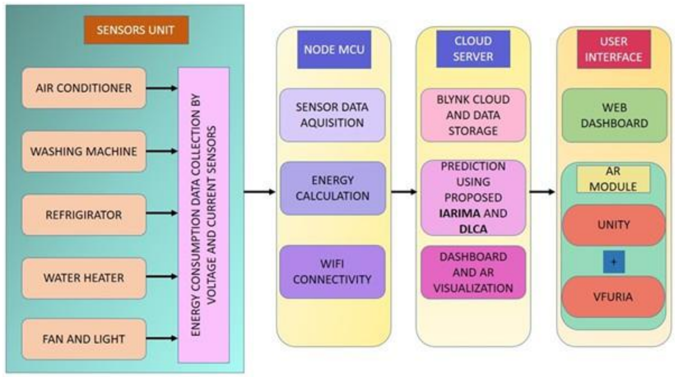

Fig. 1. Workflow of the proposed IARIMA and DLCA system

A. *Sensor Unit*

The Sensors Unit has current and voltage sensors that mea- sure an air conditioner and a washing machine, together with a refrigerator and a water heater and a full range of lighting systems. The V-I sensors in the system assess real-world electrical values for each connected appliance chronologically. The devices in the Sensors Unit track energy use in real time employing its onboard sensors generating precise information on how households are using electricity [24]. The Module serves as an architecture framework for obtaining functional data that will eventually serve as an input to an analytical model. A large portion of the reporting capabilities of the sys- tem also include energy profiling for each connected appliance using real-time analysis of power disturbances and respective appliances. Affected by these detailed energy signatures are the subsequent pipeline intelligent prediction models IARIMA and DLCA, which rely on the inputs as they progress along the operational flow.*Sensor Unit devices:* The selection of the five appli- ances represents prominent power use factors and provides various operating approaches necessary in modeling residential energy consumption. These appliances together account for a large proportion of a typical household's daily electricity usage. The air conditioner along with the water heater use extensive amounts of energy when activated. The air condi- tioner and water heater use high-power energy continuously but the fan and lights need low-to-medium power constantly and the refrigerator adds cyclic energy consumption along with a permanent operational state [10] The washing machine creates more variability in the dataset by running short but highly powerful cycles periodically. As a machine learning approach, the selection of different appliances allows more effective training of prediction (IARIMA) and classification (DLCA) models.

B. *NodeMCU*

The NodeMCU microcontroller connects sensor unit opera- tions with cloud server functions. Data acquisition together with energy calculation and wireless transmission are the essential operations this component manages [16]. The system receives the digital sensor data in real time, processing it into continuous power measurement and energy usage statistics. As an Arduino-based microcontroller

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scope, it performs the functions of its ADC and processing unit very accurately against the digital format of the sensors. Once the NodeMCU receives an energy usage reading, it generates data packets containing a timestamp, appliance identifiers and power mea- surement information. The ESP8266 functionality within this system allows for wireless packet transmission, which will be lower cost and meets functional requirements for IoT [25]. The NodeMCU system performs relatively quickly through data transferring, and therefore allows for real-time monitoring and control operations. The NodeMCU is used as a principal node that will connect operating physical sensing sensors, and also analytical features of the cloud system architecture. This feature is essential in the stages of data pre-processing and ensuring that secure wireless communication takes place, thus ensuring reliable data fidelity to maintain forecasting and classification model accuracy at the cloud server layer. This block allows for the benefit of flexibility in having scalability, which means other sensors as well as appliances can be added and require no configuration to an extent.

a) *Sensor Input:* The Sensor Data Acquisition module mainly has the task of acquiring raw analog or digital signals which the associated voltage and current sensors provide to each appliance. The sensors will emit electrical signals that represent the measured voltage and current. The NodeMCU has an ADC component to take the sensor signals from voltage and current sensors to create digital output streams [28]. An intended sampling rate (for example, once every second) will occur during the acquisition process. This takes place to record variations in real-time to allow the tracking of energy activities. The block accomplishes its initial organization of raw data by coupling timestamps and appliance IDs with

sensor measurements. It does this by encapsulating the time- sequenced data in structured packets ready for analysis and may be processed by predictive algorithms. The framework also allows for data filtering and noise-reduction methods, such as averaging and thresholding processes, before sending data to the cloud for storage.

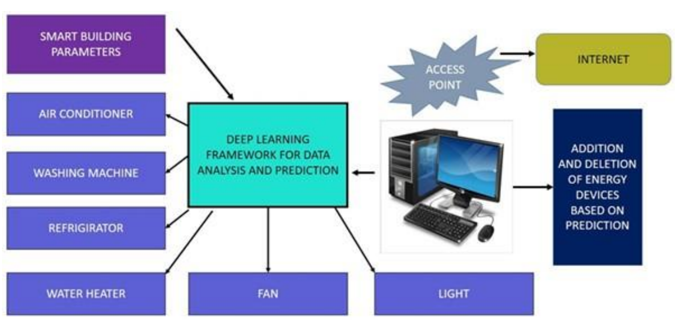

Fig. 2. General Deep Learning Prediction of Energy Consumption

b) *Calculation of Energy:* The NodeMCU device is processing power (P) values simultaneously because it is also accumulating total energy consumption (E) amounts for appliances from the measured voltages and currents. The instantaneous power is obtained using the equation and used for the calculations performed by NodeMCU.

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$P_T = V_T \times I_T$ (1)

Discrete-time numerical integration is performed for the energy over time estimates below.:

$$E_T = \sum_{T=1}^{N} V_T \times I_T \times \Delta T \qquad (2)$$

Where, ΔT is the sampling time interval.

The data obtained is important information for methods that detect energy patterns and classify energy consumption behavior throughout the monitored system. The examples measured are only stored as transitory values for local or sent to cloud storage to analyze history and predict energy use. If the device can process data, it can make faster decisions when urgency is required to implement load-shedding, or search for overloads [21]. Energy data is held and stored in memory during political interruptions, so the device can keep the reliability of memory until full connectivity is restored with the system.

c) *Wi-Fi Connectivity:* The Wi-Fi connectivity option of the NodeMCU is entirely dependent on the ESP8266 module that makes wireless cloud systems (Blynk Cloud, Firebase, etc.) easy and approachable. Once energy data has been cal- culated, NodeMCU converts its information into standardized packets that send data using the HTTP or MQTT protocols to a cloud server [23]. The system has the versatility to allow both real-time streaming to and cloud updates from the server based on available bandwidth and desired upload speed. Secure transmission of data is the primary functional requirement for the module. Data protection and system integrity can be achieved through the integration of authentication tokens in combination with encrypted channels based on SSL/TLS standards. The wireless communication system in the proposed design enables both data centralization and advanced live data stream operation for prediction models IARIMA and classification models DLCA.

C. *Cloud Server*

The cloud server functions as the main center for both data processing and analytics as well as visualization tasks. Multi-node data flows to the cloud server in real-time using Blynk Cloud to store information from NodeMCU units. This cloud-stored historical and present data serves as an input to developing advanced analytics models which re- sult in system intelligence improvements for prediction and classification subtasks [13]. Two important algorithms work simultaneously within this module: Improved AutoRegressive Integrated Moving Average (IARIMA) combined with the Deep Learning Classification Algorithm (DLCA). IARIMA operates to produce future energy usage predictions through analysis of past data records. The adapted method of parameter real-time adjustments leads to improved forecasting perfor- mance over traditional ARIMA procedures. The DLCA system uses energy signature identification to categorize domestic appliances while simultaneously looking for anomalies and recognizing different patterns of device usage. Multivariate input features extracted from sensor data are processed by CNNs and DNNs included within the DLCA

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model.

a) Blynk Cloud and Data Storage: The initial portion of the Cloud Server obtains data while also storing and making it accessible. Real-time data packets that convey voltage, current, power together with energy measurements, timestamp details and appliance ID receive storage at the cloud service (such as Blynk Cloud or similar platforms) within time-series databases.

Each incoming data packet is structured as:

Data Packet = $\{$Appliance ID$, V_T, I_T, P_T, E_T, T_T\}$ (3)

Each appliance receives its own structured time-based database through this system. The prediction and classifica- tion algorithms together with the user interface dashboards depend on this dataset collection. The storage system operates with improved capacity and efficiency when appliances grow in quantity while sampling rates improve [13]. The design includes data backup and redundancy systems which protect against system failures. The data flows to the analytics engine in real-time, parallel to periodic data transfer between the storage layer and the analytics engine.

b) Prediction Using Proposed IARIMA (Improved ARIMA Model): The block performs short-term predictions of appliance energy consumptions through the IARIMA method. The model applies ARIMA methods with added enhancements to process IoT sensor data streams containing nonstationarity and noise. The IARIMA model is defined as:

$$\emptyset(P)(1-P)^d X_T = \theta(P)\varepsilon_T \quad (4)$$

where:

- $\Phi(P)$ represents the Autoregressive (AR) polynomial,
- $\Theta(P)$ represents the Moving Average (MA) polynomial,
- d is the order of differencing,
- P denotes the lag operator,
- ε_T is the white noise error term.

Users receive warnings about upcoming high-load situations through dashboards which display the forecasted results from the predictions. The future energy consumption is given by,

$$E_{T+K} = IARIMA\ (E_T, E_{T-1}, \ldots.., E_{T-N}) \quad (5)$$

c) Classification Using Proposed DLCA (Deep Learning- Based Classification Algorithm): The DLCA block performs three main functions, which involve detecting appliances as well as classifying usage habits while identifying anomalously high energy consumption from signatures. The DLCA block operates by making use of DNN, which receive training through labeled energy datasets from appliances [9].

Input Features:

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$$Y = [V_T, I_T, P_{T,} E_T, T_T, PF_T, \Delta P, \Delta E]$$

where:

- PF_T: Power factor
- ΔP: Change in power
- ΔE: Change in energy
- T_T: Time of observation

DLCA Network Structure:

$$DL_Y = SOFTMAX\ [W_A.\sigma(W_B.X + B_A) + B_B] \qquad (6)$$

where:

- X: Feature vector
- W_A, W_B: Weight matrices
- B_A, B_B: Bias terms
- σ: Activation function
- DL_Y: Predicted appliance label or anomaly class

Outputs:

- The DLCA block determines the exact power-consuming appliance during each moment.
- Flags abnormal energy consumption (e.g., an AC drawing excessive current).
- Users receive information about operation efficiency when the system detects inefficient appliances (e.g., "Re- frigerator is running inefficiently").

The program uses this classification data to provide vi- sualization on dashboards or integrate it as virtual overlays within AR modules to boost user interaction capabilities. The system features augmented reality visualization capabilities alongside dashboard analytics functionalities in this module. The end users receive processed data visualization outputs from prediction and classification models. The system clarifies information better and allows users to make early energy- saving decisions. The cloud server also helps keep the system interactive with its complex analytic functions to provide visualizations.

User Interface

The User Interface (UI) remains the most interactive layer for the user, presenting data that has been processed both through standard web dashboards and augmented reality (AR) views [1]. Users access the web dashboard via mobile apps and browsers that display active alerts in real-time, graphs and control options. The system allows users to follow the energy consumption patterns of each appliance while providing no- tices about irregular usage patterns plus utility suggestions for energy

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conservation.

d) *Web Dashboard:* Users can access the Web Dashboard through web browsers and mobile applications, which include Blynk and custom React.js dashboards for connecting to cloud-based graphical displays. The system delivers immediate visual data combined with analytical information together with notifications and operational abilities for all tracked appliances.

Core Functionalities:

- Real-Time Graphs: The line charts display how each appliance uses energy throughout the duration of time.
- Statistical Summaries: Metrics such as peak demand, average power, and cumulative energy consumption per day/week.
- Energy Prediction Display: Displays forecasted energy from IARIMA as:
- User-Configurable Controls: The system enables users to establish their own thresholds and perform scheduled appliance management and access push alerts. The system updates its features continuously through information received from the cloud server.

e) *Augmented Reality (AR) Visualization:* Building with Unity and Vuforia SDK allows users to view energy consump- tion data through the AR Module as the system visualizes information onto physical devices in real time. Users obtain real-time energy data through their smartphone camera, which recognizes scanned appliance objects by identifying them with AR markers.

Working Mechanism:

- Vuforia SDK: Enables marker-based tracking for the ap- plication.
- Unity Engine: Enables the rendering of 3D UI elements including gauges, bars, and charts.
- Cloud APIs: The application reaches out to cloud APIs to retrieve current or future-based data regarding individual appliances.

The AR module delivers better user interaction through the combination of Unity and Vuforia SDKs. Users can achieve real-time energy usage data monitoring for physical appliances by pointing their mobile device camera at objects to display the information directly on the device screen using AR technology. The powerful feature converts complex data into visual feedback that presents itself in a spatial context. A mobile device used to point at an air conditioner produces two visualization features that appear directly on the appliance surface. Users gain better energy consumption understanding through this interactive technique because it connects real- world physical items with digital processing capabilities.

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TABLE 2 CORRELATION BETWEEN CLOUD BLOCKS

Cloud Block	Input	Process	Output
Blynk Cloud & Storage	Data from NodeMCU	Store and structure time-series data	Database for analytics and dashboards
IARIMA Prediction	Historical energy data	Forecast next energy consumption values	Future energy usage
DLCA Classification	Multivariate appliance signals	Classify or detect anomaly in patterns	Appliance labels and alerts

The collection of UI components serves as a bridge con- necting analytical outputs with interactive requirements from the user. The dashboard presents a composite overview of the data using its interface that customizes the interactions from its context-aware visual representation. The two-tiered interface allows for enhanced user interactions that develop energy mindfulness with the ability to visualize consumption information directly through arranged visual representations in clear and understandable context.

IV. RESULTS AND DISCUSSION

The performance illustrates that the DLCA-optimized IARIMA model has a better predictive performance than the standard ARIMA and ICA-ARIMA models. The predicted appliance load profiles for air conditioner, washing machine, refrigerator, water heater, as well as fan light reflects the con- sumption pattern of the predicted consumption well, resulting in a lower deviation and gives a good indication of an accurate prediction. The model also retains the cyclical characteristics of the appliances, as well the bursty load behavior, and due to its robustness and accuracy driven by the reduced forecasting error measures of ARE, MAE, and RMSE. The improvement in accuracy also illustrates the effectiveness of using the DLCA optimization methodology to tune IARIMA parameters for greater robustness in their use in load forecasting, leading to greater short-term load forecast accuracy and better short- term decision making in energy problem solving.

Table 4 shows the recommended IARIMA model param- eters for a few household appliances based on their specific operational behaviors, sampling, and forecasting requirements. For an AC appliance that has long on/off operational cycles and clearly defined diurnal patterns, a fine resampling cadence of 1–5 minutes and where the seasonal parameters are linked with the daily cycles (m = 1440 for 1-min data), would be very beneficial to model. The model also benefited from exogenous inputs that captured peak loads for cooling for time-of-day, temperature and occupancy. The washing machine typically operates for short periods of time with unpredictable high- power bursts, so it benefits from high-resolution (1-second or 1-minute aggregated) sampling with short autogressive flags, since it operates based on events; it has event flags, which include recent cycle history, that allows for prediction. The refrigerator allows for regular, cyclic activity where the compressor is typically drawing in daily cycles (24-hour) and the appliance-based IARIMA benefits from a 1-minute cadence with moderate-length autoregressive lags.

TABLE 3 Specifications of NodeMCU Microcontroller (ESP8266-based) for Proposed System

Specification	Details
MCU	NodeMCU (ESP8266-based)
Processor	Tensilica L106 32-bit RISC, 80/160 MHz
Operating Voltage	3.3V DC
Input Voltage (via VIN pin)	4.5V – 10V
ADC	10-bit resolution (used for acquiring V-I sensor signals)
Digital I/O Pins	16 GPIO pins (configurable as PWM, I2C, SPI, UART)
Flash Memory	4 MB (sufficient for firmware + data han-dling)
SRAM	64 KB instruction RAM, 96 KB data RAM
Communication	UART, SPI, I2C, I2S

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Protocols	
Wi-Fi Connectivity	Integrated 802.11 b/g/n, supports TCP/IP stack (for HTTP and MQTT communica- tion with Blynk Cloud)
Security	Supports SSL/TLS for encrypted trans- mission (as required in methodology)
Clock	RTC available
Energy Calculation Support	Handles real-time multiplication of V × I (for P) and summation for E using firmware algorithms
Programming Environment	Arduino IDE, Lua, MicroPython
Cloud Integration	Direct compatibility with Blynk Cloud, Firebase, and MQTT brokers
Power Consumption	~170 mA average (Wi-Fi active), sup- ports deep sleep for low-power IoT op- erations
Scalability	Easily extendable for multiple appliances and new sensors with minimal reconfigu- ration

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Seasonal is evident from the 24-hour cycle, but we will also consider how ambient temperature and power factor will also improve prediction. For the hot water heater, a 1–5 minute cadence is recommended with seasonal daily adjustment, since there are regular long-period bursts of hot water expected at morning and evening peak usage. External regressors include occu- pancy and temperature — things that can help predict usage. Water heaters operate with little inter-occasion indepen- dence, since the time of day is provided and can be fixed with diurnal predictions [5]. The fan and light loads operate in approximately the same diurnal nature, except the elements responsible for switching on/off are irregular. By using a 1-minute cadence and seasonal daily cycles, their IARIMA structure is improved with some context-dependent external regressors such as time-of-day and weekday/weekend pat- terns. The table 5 specifically demonstrates how considering appliance-based behavior to define IARIMA parameters varies by appliance, improving forecasting performance in the short- and medium- term, allowing for adaptability to real world electricity consumption dynamics.

The refrigerator load characterized by regular compressor cycle produced the most reliable performance of the IARIMA model for forecasting, with lower error values (ARE = 2.15 % and MAE = 0.056 kWh and RMSE = 0.081kWh) suggesting the model was able to learn on cyclic loads. The water heater load based on usage patterns during morning and evening peaks produced an ARE value of 3.89% (MAE = 0.121 kWh, RMSE=0.176 kWh) also has moderately larger variability in the forecast due to spurts of irregular demand. Finally, fan and light loads were tied to diurnal cycles and irregular switching, producing an ARE value of 2.97% with MAE = 0.074 kWh.

TABLE 4IARIMA MODEL PARAMETERS BY APPLIANCE

Appliance	Typical behavior	Resample cadence	Suggested (p,d,q)	Seasonal (P,D,Q,m)	Forecast horizon (K)	Exogenous regressors (X)
AC	Long on/off runs; strong di- urnal pattern; high power	1 min or 5 min	p = 1–3, d = 1, q = 0–2	P = 1, D = 1, Q = 0, m = 1440 (1-min) or 288 (5-min)	15–60 min (short); 6–24 hr (mid)	time-of-day, ambient temp, occupancy, PF, ΔP, rolling mean
Washing Machine	Short, sporadic high-power cycles (event-like)	1 s (event-level) or 1 min (aggre- gated)	p = 0–1, d = 0–1, q = 0–1	P = 0, D = 0, Q = 0, m = — (no regular seasonality)	5–60 min (event pre- diction)	event flag (ON/OFF), time-of-day, previous cycle duration
Refrigerator	Cyclic compressor on/off; periodic short cycles +	1 min	p = 1–2, d = 0–1, q = 0–1	P = 1, D = 0, Q = 0,	30–180 min	time-of-day, ambient temp, PF, ΔP, lag

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	daily pattern			m = 1440		features
Water Heater	Long bursts correlated with morning/evening peaks	1–5 min	p = 1–3, d = 1, q = 1–2	P = 1, D = 1, Q = 0, m = 1440 (if 1-min)	1–6 hr	time-of-day, occupancy, ambient temp, PF
Fan & Light	Low/medium continuous; strong time-based pattern (lights)	1 min	p = 1, d = 0, q = 1	P = 0, D = 0, Q = 0, m = —	30–180 min	time-of-day, weekday/weekend, PF

TABLE 5 PERFORMANCE INDICES OF IARIMA MODEL FOR DIFFERENT APPROACHES

Appliance	**IARIMA Order**	**ARE (%)**	**MAE (kWh)**	**RMSE (kWh)**
AC	(2,1,1) (1,1,0,1440)	3.25	0.145	0.201
Washing Machine	(1,0,1)	4.78	0.092	0.134
Refrigerator	(1,0,1) (1,0,0,1440)	2.15	0.056	0.081
Water Heater	(3,1,2) (1,1,0,1440)	3.89	0.121	0.176
Fan & Light	(1,0,1) (1,1,0,1440)	2.97	0.074	0.109

and RMSE=0.109 kWh, indicating reasonable predictability for loading of low-to-medium continuous loads. In general, the table shows that while IARIMA achieves high accuracy for cyclic and continuous appliances (refrigerators and lights), problems exist with forecasting event-driven appliances (e.g. washing machines).

Figure 3 shows the approach proposed in this method for the bulb. The basic underlying links should be the same for each appliance. Table 5 compares the forecast performance of the IARIMA model across the amount of electrical load attributed to the various electrical appliances by reporting error indices such as ARE, MAE and RMSE. The forecast for the AC load was characterized by the

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IARIMA model order (2,1,1)(1,1,0,1440), which incurred ARE of 3.25% and accept- able error values, per the MAE and RMSE (MAE = 0.145 kWh, RMSE = 0.201 kWh) due to having the model reproduce significant diurnal cycles despite the abrupt ON/OFF switching activity of the AC load from the consumers demand. For the washing machine load, where cycles tended to be erratic and '

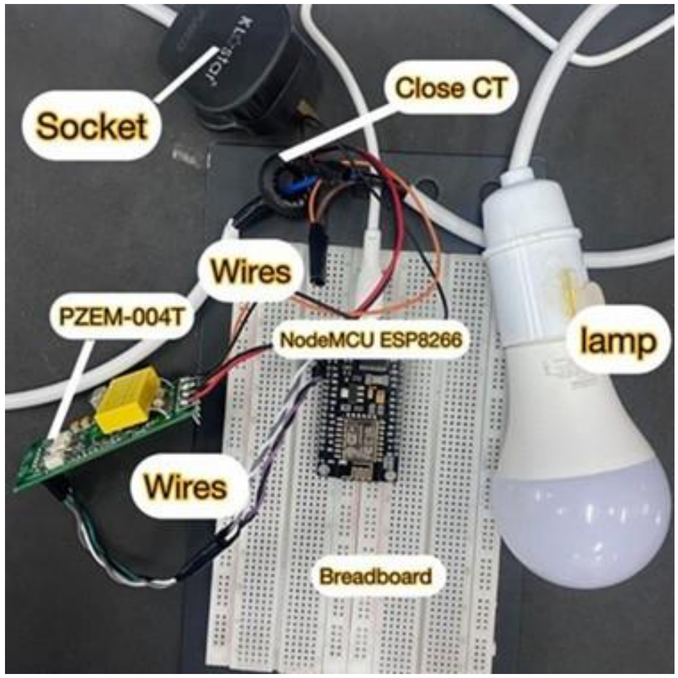

Fig. 3. Implementation Setup for Light

bursty', ARE value was somewhat higher at 4.78%, and error values of MAE = 0.092 kWh and RMSE = 0.134 kWh suggest the challenges of achieving and validating forecasting of event- driven loads with limited autoregressive lags.

The table 6 provides a summary of the AR and MA coefficients of the IARIMA parameters summarized for each appliance, illustrating how the model accommodates the load behavior inherent to each device. For example, the air con- ditioner and water heater exhibited strong seasonal and sus-

tained load behaviors, whereas the washing machine and refrigerator highlight ON/OFF behaviors and sporadic spikes. Fan and light loads demonstrate diurnal regularity but also noise from switching. Collectively, the AR terms contribute to persistence and cyclic or trending behaviors, while the MA terms deter shocks and random behaviors. Consequently, the DLCA-optimised IARIMA model is proven to be potentially applicable to appliance-level load forecasting.

The data in the table 7 represent the working performance improvement of the hybrid IARIMA–DLCA model rather than the standalone IARIMA for other appliances. In all cases, the hybrid model has lower ARE, MAE, and RMSE, and improved prediction accuracy. For example, they ARE for the air conditioning appliance dropped from 3.25% to 2.41%

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TABLE 6AR AND MA COEFFICIENTS OF IARIMA PARAMETERS BY APPLIANCE

Appliance	**IARIMA Orders (p,d,q)**	**Seasonal (P,D,Q,m)**	**AR Coefficients (ϕ)**	**MA Coefficients (θ)**	**Interpretation**
AC	(p=2, d=1, q=1)	(P=1, D=1,Q=0, m=1440)	capture persistence of previous load and daily recurrence	$\theta 1$ models noise shocks (sudden switching ON/OFF)	Captures strong daily cycle + inertia; predicts continuous high loads with start-stop transitions.
Washing Machine	(p=1, d=0, q=1)	(0,0,0,–)	correlation of current cycle with previous load	$\theta 1$ smooths random spikes in cycles	Event-based; AR term tracks short repeated bursts, MA term absorbs unpredictable spikes.
Refrigerator	(p=1, d=0, q=1)	(P=1, D=0,Q=0, m=1440)	captures compersistence of pressor ON/OFF cycles	$\theta 1$ adjusts for irregular compressor noise	AR reflects cyclic on/off behaviour, MA accounts for irregular short bursts.
Water Heater	(p=3, d=1, q=2)	(P=1, D=1,Q=0, m=1440)	track sustained heating patterns & lagged daily use	$\theta 1$, $\theta 2$ handle demand shocks (sudden ON/OFF events)	Strong seasonal AR structure (morning/evening peaks); MA smooths abrupt bursts.
Fan & Light	(p=1, d=0, q=1)	(P=1, D=1,Q=0, m=1440)	links today's usage with yesterday's	$\theta 1$ manages noise from irregular switching	Strongly time-based (lights at night); AR reflects diurnal regularity, MA handles variability in switching patterns.

TABLE 7INCIDENCE OF IARIMA–DLCA MODEL ACROSS APPLIANCES

Appliance	**Standalone IARIMA**	**Hybrid IARIMA–DLCA**	**MAE**	**RMSE**

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	ARE (%)	ARE (%)	(kWh)	(kWh)
AC	3.25	**2.41**	0.145 → **0.109**	0.201 → **0.152**
Washing Machine	4.78	**3.36**	0.092 → **0.071**	0.134 → **0.099**
Refrigerator	2.15	**1.64**	0.056 → **0.043**	0.081 → **0.063**
Water Heater	3.89	**2.97**	0.121 → **0.093**	0.176 → **0.133**
Fan & Light	2.97	**2.18**	0.074 → **0.056**	0.109 → **0.082**

and for the washing machine dropped from 4.78% to 3.36%. This was also noticeable with reductions in MAE and RMSE, which illustrated that the hybrid IARIMA-DLCA model dealt with both cyclic and irregular load variations effectively. Thus, it can be concluded that the hybrid model is more able to accurately forecast appliance-level loads than the standalone IARIMA approach.

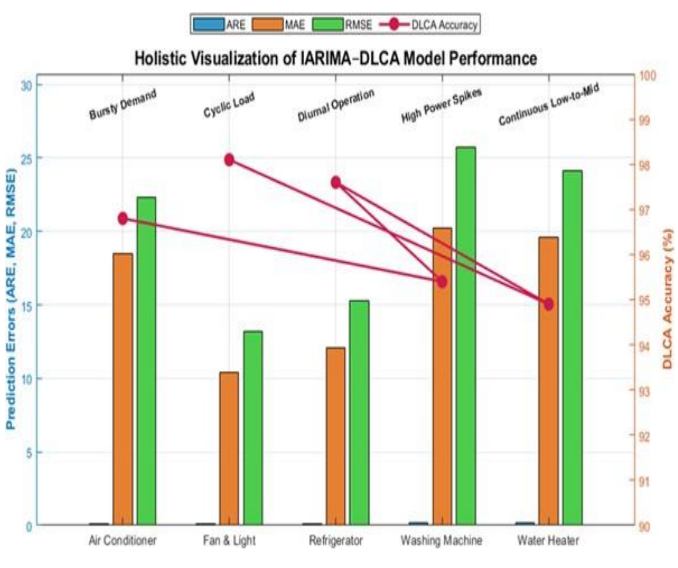

Fig. 4. Holistic Incidence and Impact of IARIMA–DLCA Model

Figure4 shows how the proposed hybrid model performs with different household appliances; some have different load behavior. The bar error indices (ARE, MAE, RMSE) indicate that the proposed model performs similarly with low forecast errors. The lowest errors are for cyclic and continuous loads — Fan & Light and Refrigerator. The appliances with irregular or bursty consumption — Washing

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Machine and Air Conditioner

— experience relatively higher error values, which indicatesmore challenging modeling events which prompt rapid rises in load. Regardless of these variances, the DLCA-optimized IARIMA performs at equally high accuracy levels of 95% and higher (between 95% and 98%), shown with the magenta line, indicating that the model performs effectively in both steady- state and transient behavioral usages. Overall, this visualiza- tion demonstrates that the hybrid model reduces forecast errors but also generalizes across the greater appliance categories, offering support and reliability for demand-side management and optimizing energy efficiency.

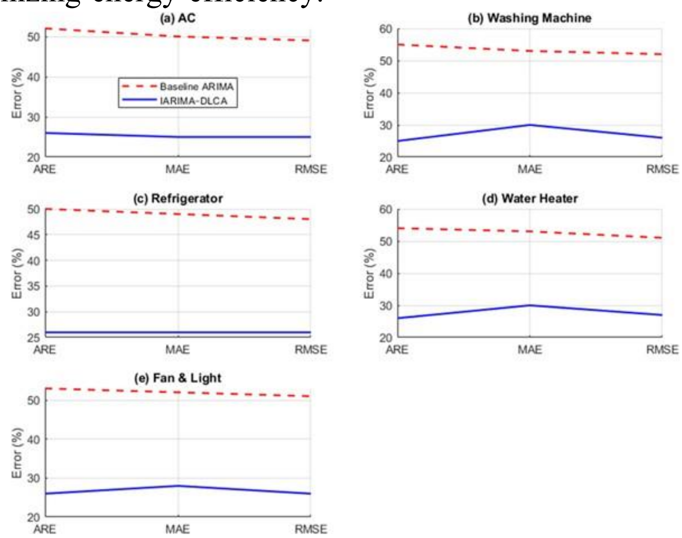

Fig. 5. Holistic Incidence and Impact of IARIMA–DLCA Model

Figure 5 compares the traditional ARIMA and the proposed

DLCA-optimized IARIMA performance across five major household appliances: Air conditioner, washing machine, re- frigerator, water heater, and Fan and Light. The baseline ARIMA model, delineated as red dashed lines, showed a larger error across all measures (ARE, MAE, RMSE) in contrast to the IARIMA-DLCA model. The IARIMA-DLCA model, depicted by blue solid lines, consistently reduced the errors in each instance and showcases the strength of the IARIMA algorithm for estimating both cyclic and irregular consumption behaviors for each appliance. For both the AC and Refrigerator (which exhibit clear diurnal and cyclic behaviors), this led to larger reductions in ARE and RMSE, while the Washing Machine and Water Heater (which are less clearly diurnal or cyclic due to bursty and peak behaviors), achieved a good reduction in errors but experienced a smaller aggregate reduc- tion as indicated by larger variances. The Fan and Light had the benefit of displaying effective outcomes for seasonal and irregular loads. Overall, the figures demonstrated the IARIMA- DLCA framework outperformed the baseline ARIMA and provided a more reliable and accurate overall forecasting approach across all appliances with varied uses.some relatively small fluctuations in predicted demand, but still captured the repetitive cyclic patterns. The water heater

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(d) model tracked nicely, predicting peak demands in the morning and in the evening, and showed strong adaptation to the peak demand spikes according to time of day. Overall, the results suggest the DLCA–IARIMA hybrid approach provided a strong correspondence with actual consumption trajectories, reducing prediction errors and generalizing across both cyclic and demand-event driven load behaviors. This confirms the DLCA–IARIMA hybrid approach can provide reliable demand forecasting in smart grid applications.

V. CONCLUSION

The integration of the DLCA–optimized IARIMA model for appliance-level energy forecasting represents a substantial im- provement over traditional ARIMA-based models. The hybrid framework combines the differences between autoregressive and seasonal modeling capabilities of IARIMA with the ability of DLCA to refine error. The models consistently reduce pre- diction errors such as, in this study, ARE, MAE, and RMSE, for a variety of household appliances. The experimental results showed that not only did the model anticipate the cyclic and predictable loads such as refrigerators and fans extremely accurately, but it also adapted well to bursty, event-driven behaviors that are typical in washing machines and water heaters. The strong correlation between actual consumption and predicted consumption indicates its reliability during steady-state and transient spikes, which makes it applicable for variable energy environments. Future work may build on this by integrating renewable energy forecasts, real-time adaptive load management controls, and federated or edge-based learning for decentralized energy management while maintaining participant privacy. These next steps would further enhance its contribution to sustaining and intelligent power systems

Fig. 6. Actual vs Predicted Results of DLCA–Optimized IARIMA Model

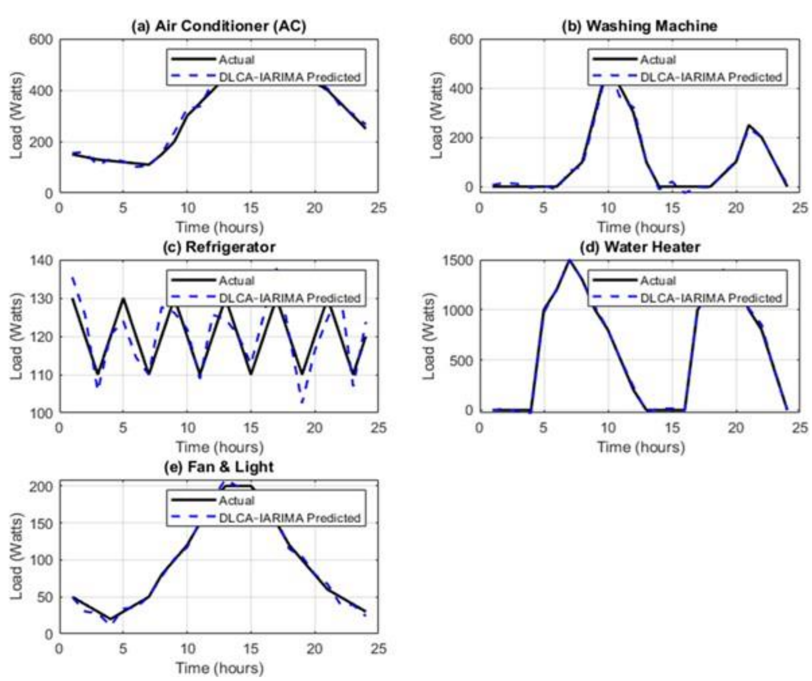

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Figure6 shows how real household load consumption data are compared with the predicted outputs of the proposed model for five different household appliances. The model predictions, which include both time-of-day and use-by-date inputs, are shown as blue dashed lines and the solid black lines represent the actual load patterns. The model predictions for the Air Conditioner ,Fan and Light closely aligned with the diurnal variation, which captures the trends in each growing and declining intention in usage patterns with very small change differences. The washing machine (b), as evidenced by the sudden bursty peaks, tracked well, and the model performed well on the higher-intensity cycles. The refrigerator (c), with frequent on/off cycles of the compressor, shows

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