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Research Article

# Fabrication of Smart Meter for Accurate Use in Home and Industry

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**A B S T R A C T**

This study addresses the challenges posed by conventional energy meters, which rely on manual readings, leading to human errors and inefficiencies. In response to this, a battery-powered smart meter was developed utilizing an STM32 microcontroller, ADE7758 and STPM32 metering integrated circuits (ICs), SIM and ESP32 communication modules, along with a MYSQL database. Real-time energy data from both single and three-phase appliances were collected, and their energy consumption, errors, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) were quantified. The model demonstrated an acceptable accuracy level, with an estimated MAE of approximately 2.912 units and an estimated RMSE of around 4.048 units, particularly in predicting motor power consumption. Additionally, ARIMA forecasting was applied to a three-phase asynchronous motor, revealing an average active motor power of 250.95 watts, indicating precise results over time.

## INTRODUCTION

While energy is necessary for every business, controlling and managing its use can be difficult [1]. increased energy prices, volatile markets, increased demand, and stringent government regulations have all made this problem more urgent. In response to these issues, businesses have created intelligent Energy Management Systems (EMS) that can assist in lowering costs, boosting productivity, and satisfying energy requirements [2]. The Internet of Things (IoT) is crucial in this regard in today's interconnected society. IoT refers to the process of tying up items or things that include sensors, software, and other technological components to share data over the Internet with other systems and devices. By 2025, it is anticipated that there will be three times as many devices connected with IoT, making it one of the most important inventions of the twenty-first century. IoT enables communication between objects, people, and processes by using embedded devices to link common appliances, cars, and even baby monitors to the Internet [2].

In the realm of energy management, the advent of smart metering technology has brought about significant advancements. However, despite these strides, there exist critical knowledge gaps that impede the realization of the full potential of smart meters. This study is driven by a commitment to address these specific gaps in the existing literature. Firstly, the current body of research predominantly focuses on basic consumption analyses, lacking a nuanced understanding of intricate patterns and variations in energy usage. This study aims to contribute to the field by delving deeper into subtle consumption behaviors, providing a more comprehensive foundation for effective energy management. Secondly, proactive load forecasting, a crucial aspect of grid optimization and disruption prevention, remains an underexplored area in smart metering. This research seeks to fill this gap by integrating advanced forecasting models, particularly the ARIMA model, into smart metering systems. Moreover, the integration of sophisticated time-series analysis techniques, such as ARIMA, for precise load forecasting and anomaly detection is a novel approach in smart metering. By addressing this gap, the study aims to enhance the accuracy and reliability of smart meter predictions. The literature also lacks comprehensive investigations into the detailed behaviors influencing energy consumption. This work endeavors to bridge this gap by conducting meticulous analyses of consumption patterns, shedding light on factors that may have been overlooked in prior research. Efficient processing of vast energy datasets is essential for meaningful insights. The current state of research lacks a thorough exploration of optimized data processing techniques in the context of smart metering. This study aims to contribute novel methods for processing energy data, ensuring more effective decision-making. By focusing on these specific knowledge gaps, our research aspires to propel the field of smart metering forward, providing valuable insights to optimize energy management systems and foster sustainable energy consumption practices.

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Power consumption per consumer unit has traditionally been calculated by hand. Going to the location where the meters are located and personally recording data regarding power use from each consumer unit or meter is the technique that this involves. This method, which has been in place for some time, requires meter readers to visit meters regularly and collect usage data [3]. Automation of measurement acquisition has become possible due to recent advances in communication and processing technologies [4]. Real-time electricity consumption measurements are frequently recorded by smart meters, which then relay this data to households and energy providers [5]. Grid frequency management, energy metering, scheduled load shedding, control center computers, and terminal devices have all made use of smart metering. The raw voltage (V) and current (I) waveforms are measured at sample speeds compatible with this function to calculate the root mean square (RMS) values. The following metrics are frequently returned by smart meters after local analysis of the raw data: active power (P), reactive power (Q), apparent power (S), consumed electrical energy (E), and the phase angle (cos/) between voltage and current. In multi-phase electrical installations, parameters can only be accessed as an aggregate or are returned individually for each phase [6].

Time-series and regression analysis, fuzzy logic, genetic algorithms, support vector machines, artificial neural networks, and genetic algorithms are a few of the techniques that have been proposed for the analysis and load forecasting of data from smart meters. To get above the limitations of a single technique, hybrid approaches also use two or more techniques [7]. By including econometric factors and expanding the model to a wider horizon, short-term load forecasting (STLF) can be converted into medium-term load forecasting (MTLF) and long-term load forecasting (LTLF). The following few days to months' worth of loads are typically predicted using MTLF. Planning for generation expansion gains from using long-term long-term funding (LTLF), which is applied for several months to years. STLF can be transformed into MTLF and LTLF by adding econometric variables and expanding the model to a longer horizon. To predict loads for the upcoming days to months, medium-term load forecasting, or MTLF, is widely employed [7].

Kumari et al. present a smart and optimal power allocation strategy to the utility by utilizing a global system for automated, remote energy meter reading that is built on mobile communication modules. The targeted gadget is put on the customer's property, together with the energy meter. A GSM module establishes smart communication between the consumer and the service provider by calculating energy expended at different rates and periods. To identify the optimal service provider allocation to satisfy the goal function, an artificial neural network with backpropagation is employed. Smart energy metering is a ground-breaking idea that helps reduce energy costs while also facilitating proper repayments, optimal power consumption based on tariffs for different times of the day, and more flexible and reliable theft control [8]. A microcontroller unit is responsible for managing data, communication, and control (MCU). Analog-to-digital converters (ADC) transform analog sensor data into digital representation, while radio frequency integrated circuits enable wireless communication [9]. Displays, sensors, and cable connections are managed by the display driver, sensor interface, and communication interface. To check for tampering, sensors from micro-electromechanical systems (MEMS) may also be employed. The integrated circuits that smart meters can have vary depending on the manufacturer, features, and local regulations [10].

The subject of data analytics and smart meters had a substantial knowledge gap before the introduction of ARIMA for forecasting. The majority of previous research focused on basic consumption analysis, with little attention paid to in-depth assessments of subtle patterns or load predictions. Our work created a novel approach that combines the ARIMA idea with meticulous data processing to close this gap. By taking this action, we aimed to enhance the efficiency and dependability of smart metering systems, facilitating proactive load forecasting and more precise identification of anomalous consumption patterns [11].

To achieve this, a KiCad smart meter PCB was created, including crucial parts for data gathering and energy monitoring. Data on the energy consumption of three-phase motors and home appliances, such as computers, stereo systems, electric irons, and room heaters, were concurrently gathered and saved as single-phase and three-phase energy consumption data [12]. There will be an energy assessment board calibration. The STM32 microcontroller will be utilized for the processing of the gathered data. The ESP32 and SIM7600 modules will enable data relaying, and sending processed data to a centralized server. Structured data will be stored in a centralized database using PhpMyAdmin. The ARIMA model will be used to analyze the energy data to find patterns, trends, and projections of future energy use. Industries can control energy consumption, improve operations, and support sustainability efforts by adopting this technology.

This study introduces a distinctive contribution to the field of smart metering and energy management through the development of a low-cost, versatile smart metering device. The novelty of the study lies in its integrated design, combining components such as the STM32 microcontroller, ADE7758 and STPM32 metering ICs, SIM and ESP32 communication modules, and a MYSQL database. This device not only demonstrates versatility by collecting real-time energy data from both single and three-phase appliances but also ensures high precision in calibration, achieving a remarkable 0 percent variance. The innovation extends to connectivity options, allowing data transmission through both SIM and Wi-Fi, providing adaptability to diverse environments. The study addresses a significant knowledge gap by explicitly recognizing the scarcity of in-depth analyses in current smart metering approaches and proposes a solution with advanced analytical techniques, including the application of ARIMA forecasting. Emphasizing sustainability, the smart meter offers industries a tool to manage energy usage effectively, optimize operations, and contribute to broader sustainability goals. In summary, this study's novelty lies in its holistic approach, combining hardware innovation, precise measurement, advanced analytics, and a focus on accessibility and sustainability in the realm of smart energy management.

## METHOD

Data on energy use for both single and three-phase appliances can be collected by the smart meter. A three-phase electricity supply was supplied to the smart meter by the ADE7758-based energy metering evaluation board. The STPM32-based evaluation board connects the smart meter to the single-phase energy source. The STM32 microcontroller is used for energy data processing. Whereas single-phase evaluation boards are connected via UART, three-phase evaluation boards are connected to the microcontroller via the SPI protocol. The SIM7600 is used to send energy data to the database. Figure 1 shows the meter's flowchart.

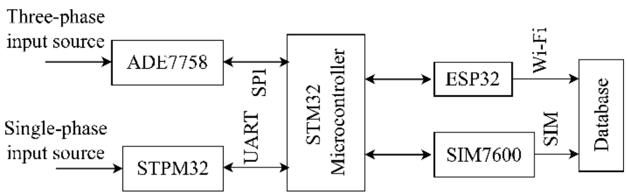


Figure 1. Simple flowchart of the smart metering system developed for the study

## *Development of boards*

### *Overview schematic of smart metering systems*

Single and three-phase appliance metering is supported by this smart meter. Different parts make up the Smart meter PCB depicted in Figures 2a and 2b. These parts include an STM32 microcontroller, voltage regulators, battery holders (18650), communication modules (ESP32 and SIM7600), LEDs, resistors, capacitors, connection pins, and communication protocols (SPI and UART). KiCad, an open-source PCB design program, and electrical schematic tools were used in the PCB design process. The STM32CubeIDE is used to generate the PCB firmware for smart meters. Energy data is processed by the STM32 microcontroller in the smart meter. For compact devices that run on batteries, the STM32 microcontroller has enough processing capability. When compared to other microcontrollers in the industry, such as Arduino and AVR, this microcontroller's strong capability demonstrates its appropriateness for use in Internet of Things applications.

STM32 microcontrollers have a large number of serial and parallel communication peripherals that enable them to communicate with different electronic components [13]. STM32CubeIDE, an integrated development environment for STM32 that includes peripheral configuration, code generation, code compilation, and debugging tools for all STM32 microcontrollers and microprocessors, is used to program STM32 microcontrollers. It incorporates an STM32CubeMX project's capabilities. The microcontrollers are configured and the necessary code is generated by the STM32CubeMX tool. A Universal Asynchronous Receiver Transmitter (UART) is used to connect the STPM32 metering integrated circuit (IC) for single-phase energy metering to a smart meter PCB, enabling the transmission and reception of energy data. A Serial Peripheral Interface (SPI) connects the smart meter PCB to the three-phase metering IC, ADE7758. The ADE7758-based evaluation board and the smart meter PCB may exchange serial data thanks to this interface. Data can be sent simultaneously in both directions because of its duplex mode of operation [14].

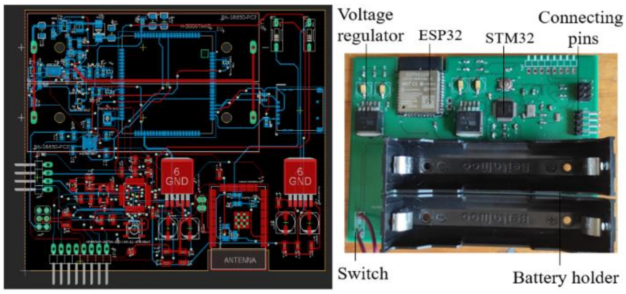


Figure 2a: Smart meter PCB design　　Figure 2b: Assembled smart meter PCB

Figure 2. Assembled smart meter PCB: (a) Picture of smart meter PCB designed in Eagle, and (b) Picture of smart meter PCB after assembly of components

### *Development of single-phase and three-phase evaluation boards*

To gather single-phase energy data from single-phase devices, this project makes use of the STPM32-based evaluation board, which is depicted in Figure 3b. Instantaneous voltage and current waveforms are provided by the STPM32, which also computes the root mean square (RMS) values of active, reactive, apparent power, and energy. The STPM3x is an advanced mixed-signal IC family tailored for precise power and energy measurement in power line systems, utilizing sensors like Rogowski coils, current transformers, or shunt current sensors. It offers a comprehensive set of features, including the calculation of RMS values for voltage and currents, active, reactive, and apparent power, and energy. The analog section encompasses programmable gain amplifiers, sigma-delta ADCs, voltage references, and other components, while the digital section features digital filtering, a hardwired DSP, and communication interfaces (UART or SPI). Noteworthy is its exceptional accuracy, boasting less than 0.1% error over a wide dynamic range for both active and reactive power. It meets or exceeds standards such as EN 50470-x, IEC 62053-2x, and ANSI12.2x for AC-watt meters. The STPM3x allows fast digital system calibration across its current dynamic range, and its operational capabilities encompass various aspects, including instantaneous and averaged power, voltage/current RMS, sag and swell detection, and overcurrent monitoring. With a range of programmable features, precision ADCs, and reliable performance characteristics, the STPM3x plays a pivotal role in ensuring high-accuracy power measurements for the smart metering system. STM32 microcontroller in smart meter PCB is integrated with STPM32 through the UART interface. Stroia et al. demonstrated the use of STPM32 in smart metering [15].

This project uses an ADE7758-based three-phase evaluation board, shown in Figure 3b, to collect three-phase energy data from three-phase appliances. The ADE7758 Evaluation Board stands as a versatile assessment platform for the ADE7758 metering IC, offering user-friendly configuration via a PC's parallel port and a fully isolated data interface. Tailored for energy meter applications, the board emulates real-world scenarios by connecting to test benches or high-voltage circuits. Supporting various current transducers, it integrates on-board resistor divider networks for precise line voltage attenuation. With two external 5 V power supplies, including one for isolation, and compatibility with 3-phase configurations, the board ensures accurate measurements. It boasts high accuracy, meets multiple industry standards, and provides comprehensive energy data, including active, reactive, and apparent energy, along with voltage and current rms. The board's two pulse outputs and digital calibration enhance functionality, and on-chip programmable thresholds enable effective detection of critical power conditions. ADE7758 was utilized in smart energy monitoring by Guimarães et al [16]. To create a three-phase energy meter, the STM32 microcontroller in the smart meter PCB is integrated with the ADE7758-based evaluation board via the SPI protocol.

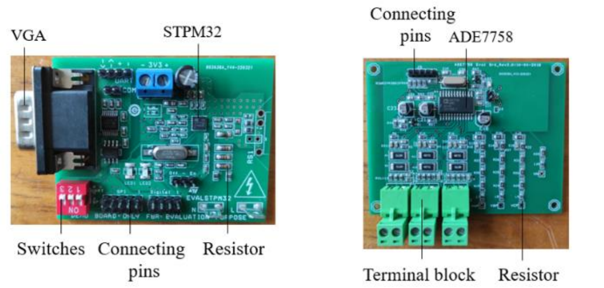


Figure 3a: Assembled STPM32 PCB    Figure 3b: Assembled ADE7758 PCB

Figure 3. Assembled metering evaluation boards: (a) STPM32 evaluation board after assembly, and (b) ADE7758 evaluation board after assembly

*Development of a smart meter communication module*

SIM 7600 and ESP32 modules make up the energy meter communication system. While SIM 7600 employs 4G SIM connectivity to communicate energy usage statistics to the database, the ESP32 module features integrated Wi-Fi. The potential use of the smart meter in various locations led to the selection of two communication modules. 4G SIM is advantageous for customers who are unable to connect to Wi-Fi. The database used to manage the energy data was created using PhpMyAdmin. Real-time energy data may be easily stored and retrieved with its ease of construction.

*Experiments*

Data collection and smart meter calibration were conducted using laboratory equipment supplied by Elettronica Veneta S.p.A. The power needed by the various appliances was controlled by the AV-1/EV power supply (Elettronica Veneta S.P.A., Italy). Single-phase and three-phase smart metering evaluation board integrated circuits (ICs) were calibrated using the meters, power supply, and three-phase asynchronous motor from Elettronica Veneta. Three-phase energy data on consumption was gathered using a three-phase asynchronous motor (Mod. M-4/EV) connected to a generator with independent excitation (Mod. M1-2/EV). This induction motor has a duty-type S1 rating, meaning it can run continuously at a set load for long enough to bring the machine up to thermal equilibrium. 500W, 415V, and 1.3A star connections are its ratings [17].

Line voltage and line current are used in this instance to gather statistics on energy use. The information is then utilized to calculate apparent power, active power, and reactive power—all of which are necessary to understand how much energy the motor uses. Power consumption is calculated using several variables, some of which were taken from the motor's nameplate, such as the power factor of the motor. Utilizing a 1500W Mika room heater, a 240W HP Compaq 6200 Pro SFF Desktop PC, a 750W LG electric iron box, a 150W Sayona audio system, and other devices, hours of energy use were recorded.

The comprehensive data collection approach involved precise measurements of line voltage and line current, ensuring a thorough examination of the three-phase motor's energy consumption characteristics. The analysis encompassed crucial parameters such as apparent power, representing the total power flow; active power, denoting the real power consumed; and reactive power, indicating the non-working power that oscillates between source and load. These insights were fundamental for understanding the motor's overall power dynamics and performance. Additionally, meticulous attention was given to factors influencing power consumption, including the power factor obtained from the motor's nameplate. This multifaceted data collection strategy provided a holistic view of the three-phase motor's energy usage patterns, offering valuable information for the subsequent calibration and testing processes of the smart metering system. Concurrently, various household appliances were systematically monitored, ranging from the high-power Mika room heater to the energy-efficient HP Compaq 6200 Pro SFF Desktop PC, facilitating a diverse and representative dataset for the study.

## RESULTS AND DISCUSSION

***Voltage and current calibration in evaluation boards***

The register values of the metering integrated circuit and the actual voltage readings from a reference power supply meter were used to calibrate the voltage in the ADE7758. As seen in Figure 4a, the data were entered into a table and utilized to create a graph that depicts the equation describing the relationship between the variables. A linear equation, $y = 2806.3x + 262.15$, governs the variables. To receive precise voltage readings from the smart meter, the firmware is updated using the given equation. The register values from the ADE7758 metering IC are shown on the y-axis, and the actual voltage levels are represented on the x-axis. Similar to voltage, the current was calibrated in ADE7758 [18]. The current reading from the reference meter and the associated register values on the serial monitor were noted. A linear relationship between the register values produced by the smart meter and the actual current measurements is depicted in Figure 4b's graph. The linear equation $y=48736x + 1842$ represents the linear relationship between the two variables.

The register values of the metering integrated circuit and actual voltage readings from a reference power supply meter were used to calibrate the voltage in the STPM32. As seen in Figure 4c, the variables follow a linear equation: $y = 16.093x + 34.735$. The register values from the smart meter are displayed on the y-axis, while the actual voltage values are displayed on the x-axis [19]. The register values of the smart meter were compared to the readings from a reference meter. As seen in Figure 4d, a graph illustrating the variables' linear relationship was created using the results. Equipped with the equation $y = 139320x + 1729.2$, a linear graph is produced.

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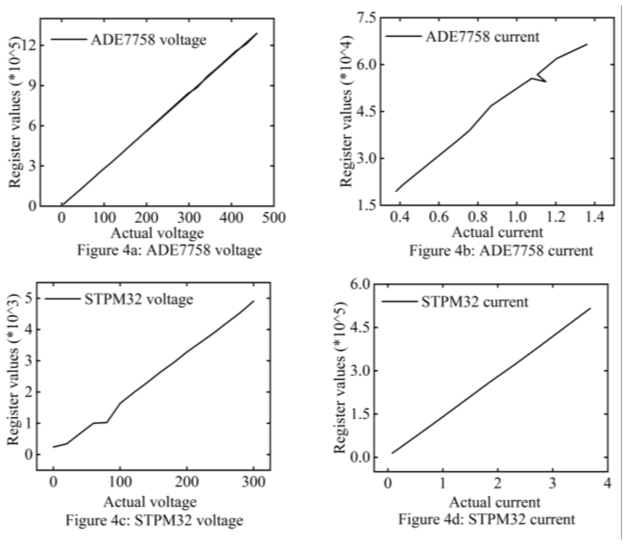


Figure 4. Calibration of voltage and current in metering evaluation boards (ADE7758, and STPM32): (a) Calibration of voltage in ADE7758, (b) Calibration of current in ADE7758, (c) Calibration of voltage in STPM32, and (d) Calibration of current in STPM32

### *Time series analysis for the appliances*

A time series analysis of the active power of the appliance reveals that there is a common pattern, seasonal variation, or autocorrelation among the data points collected over some time. The information is displayed in Figure 5 as a graph showing the active power of appliances concerning the index number. The largest power user is the 1500W Mika room heater. The 150W Sayona audio system is an energy-consumptive little device. The energy consumption data for the 750W LG electric iron box is dispersed throughout the graph, with the majority of it being below zero because of the thermostat's constant on-and-off cycles.

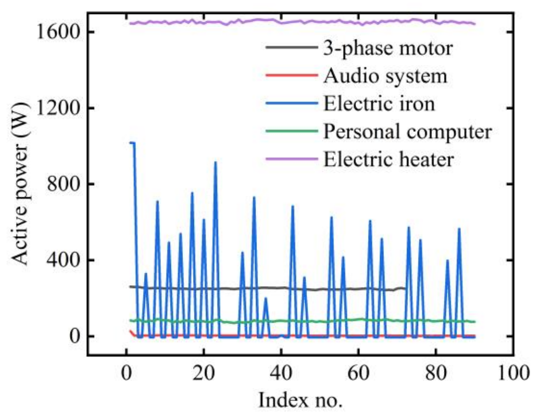


Figure 5. Time series plot: Active power consumption of power by the single-phase and three-phase appliances used in the experiment

The validation process involved a meticulous assessment and calibration of the smart meter's components, particularly the STPM32 and ADE7758 metering integrated circuits (ICs). Calibration of the ADE7758 required a comparison of register values with actual voltage and current readings obtained from a reference power supply meter. This calibration process ensured the establishment of precise linear relationships and conversion formulae for voltage and current measurements. Similar linear equations were derived for the STPM32 metering IC. The accuracy of these equations was confirmed through a thorough validation of the smart meter's relationship with the reference voltage and current. The results, demonstrating a 100.00 percent variance between the reference and smart meter readings, affirmed the high accuracy of the measurements taken by the smart meter. This robust validation process provided a foundation for the subsequent analyses and forecasting models, ensuring the reliability and dependability of the smart meter's performance.

Table 1. Numeric accuracy results of the calibration and validation showing voltage and current readings in smart meter and reference meter

| Index | Vref. | Vsmart | Iref. | Ismart |
|---|---|---|---|---|
| 1 | 239.81 | 239.38 | 6.528 | 6.872 |
| 2 | 241.98 | 239.01 | 7.040 | 6.879 |
| 3 | 239.58 | 239.18 | 6.603 | 6.912 |
| 4 | 241.50 | 239.11 | 6.899 | 6.884 |
| 5 | 239.67 | 238.12 | 6.890 | 6.948 |
| 6 | 239.48 | 239.10 | 6.620 | 6.936 |
| 7 | 241.77 | 239.13 | 7.024 | 6.920 |
| 8 | 240.13 | 239.07 | 6.785 | 6.961 |
| 9 | 241.75 | 239.80 | 6.543 | 6.950 |
| 10 | 241.81 | 238.51 | 6.802 | 6.951 |

The graphs in Figures 6a and 6b verify the relationship between the meters and demonstrate the accuracy level of the smart meter. The smart meter's precision in taking readings is demonstrated by the 100.00 percent percentage difference between its voltage and current and the reference voltage and current.

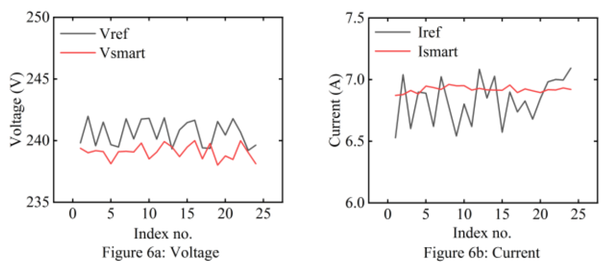


Figure 6 Validation of the relationship between the reference meter and smart meter: (a) Validation of Voltage(V) readings in the smart meter compared to the reference meter, and (b) Validation of Current(I) readings in smart meter compared to reference meter

### *Results of ARIMA*

*Error analysis*

Table 2 shows the data used for error analysis. This study Calculates the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) using equation (1) and (2) respectively.

Table 2. Data used for error analysis

| Index | P(Active) | Forecast |
|---|---|---|
| **1** | 260.6794864 | 249.798 |
| **2** | 259.8415145 | 249.955 |
| **3** | 259.1725696 | 250.091 |
| **4** | 256.1425517 | 250.208 |
| **5** | 253.0235726 | 250.309 |
| **6** | 252.6417918 | 250.397 |
| **7** | 252.8759345 | 250.472 |
| **8** | 253.6351166 | 250.537 |
| **9** | 252.3212424 | 250.594 |
| **10** | 251.5732152 | 250.642 |
| **11** | 252.0120230 | 250.685 |
| **12** | 252.5953378 | 250.721 |
| **13** | 250.4713191 | 250.752 |
| **14** | 250.4035616 | 250.779 |
| **15** | 250.0262881 | 250.803 |
| **16** | 249.1630945 | 250.823 |
| **17** | 247.6628078 | 250.840 |
| **18** | 247.5625538 | 250.855 |
| **19** | 249.9006961 | 250.869 |
| **20** | 250.5234186 | 250.880 |
| **21** | 250.2303177 | 250.889 |
| **22** | 249.7948914 | 250.898 |
| **23** | 248.5159342 | 250.905 |

$$MAE = \frac{\sum_{i=1}^{n} \left| y_i - x_i \right|}{n} \tag{1}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left( x_i - y_i \right)^2}{n}} \tag{2}$$

where $y_i$ is the forecast value and $x_i$ is the true value or P(active) as obtained in Table 2, while n is the total number of data points, which is 23. The average absolute difference between the predicted and actual values is measured by the MAE. Equation 1 illustrates that the average fundamental error in this instance is roughly 2.912 units. The average squared difference between the predicted and actual values is measured by the root mean square error, or RMSE [20].

According to equation 2, the RMSE in this instance is around 4.048 units. To summarize, the projections produced by the ARIMA model deviate from the actual values by an average of 2.912 units. According to the RMSE, the model's typical prediction error is approximately 4.048 units. These error metrics shed light on how well the ARIMA model predicts the motor's active power and how accurate it is. Better model performance is often indicated by lower MAE and RMSE values; however, the context and needs of the particular application should also be taken into account when interpreting the findings. Based on the data gathered for the period, the model offers comparatively accurate predictions [20].

*Parameter estimates*

The final parameter estimates of an ARIMA model are shown in Table 3 together with the statistical measures that go along with them. The estimated coefficient for the AutoRegressive (AR) term of lag 1 is denoted by the AR(1) coefficient, which in this instance has a value of 0.8637. The standard error (SE Coef) of this estimate, which accounts for random fluctuations in the data, is 0.0700 [21]. The statistical significance of the AR(1) coefficient is indicated by the t-value of 12.33 and the associated p-value of 0.000, indicating a significant influence on the model's predictions. In a similar vein, the Moving Average (MA) term of lag 1's estimated coefficient, or MA(1) coefficient, has a value of -0.315. This estimate has a standard error of 0.120. There is a p-value of 0.011 and a t-value of -2.63. The statistical significance of the MA(1) coefficient is further demonstrated by these results [21]. The intercept of the ARIMA model is the constant term, with a coefficient estimate of 34.200 and a standard error of 0.268. The constant term is statistically significant and has a considerable impact on the model, as indicated by the constant's t-value of 127.49 and p-value of 0.000.

An additional part of the ARIMA model is the estimated mean of the time series, which is shown as 250.95. An important metric for determining the time series' overall level is the mean value. Small p-values (less than 0.05) indicate statistical significance in parameter estimations, and they provide a substantial contribution to the predictions of the ARIMA model. These parameter estimates—the constant, mean, MA(1) coefficient, and AR(1) coefficient—will be used by the ARIMA model to help it make precise predictions and reveal underlying patterns in the time series data. To create a more accurate forecasting model, statistically significant parameters are essential for capturing the dependencies and features of the time series [20].

Table 3. Final estimates of parameters

| Type | Coef | SE Coef | T-value | P-value |
|---|---|---|---|---|
| **AR(1)** | 0.8637 | 0.0700 | 12.33 | 0.000 |
| **MA(1)** | -0.315 | 0.120 | -2.63 | 0.011 |
| **Constant** | 34.200 | 0.268 | 127.49 | 0.000 |
| **Mean** | 250.95 | 1.97 | - | - |

*Active motor power consumption and prediction*

The motor has a mean active power of 250.95 Watts. When the motor is operating at full load, its hourly power consumption is 0.25 kWh. For the motor, the daily consumption is about 6 kWh. A time series plot of the three-phase motor's active power consumption is displayed in Figure 7a. The predicted upper and lower bounds for power consumption based on the trend of the recorded values are displayed in Figure 7b. The motor's mean active power is shown by the midline. The motor's active power is shown versus time on the graph with a 95 percent confidence level [22]. The range of values that the actual active power mean is most likely to fall within is shown by the lower and upper limit values. The motor's maximum and lowest active power consumption limitations are depicted by the blue and red plot lines, respectively, while the middle line indicates the average active power consumption [5].

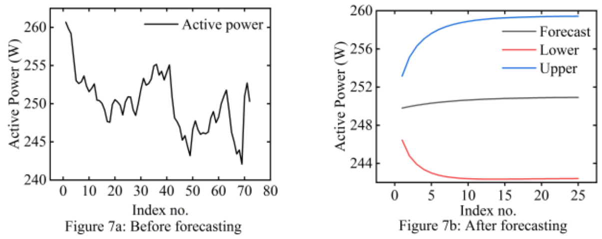


Figure 7. Time series plot: (a) Active power of three-phase asynchronous motor before forecasting with ARIMA, and (b) Active power of three-phase asynchronous motor after forecasting with ARIMA

In comparative evaluation, ARIMA generally surpasses simpler techniques like SMA and SES when confronted with intricate time series patterns, trends, and seasonality; however, its efficacy hinges on the inherent characteristics of the data. When pitted against neural network-based methods such as LSTM, ARIMA may be outperformed in instances of highly nonlinear and intricate patterns, with LSTMs excelling, particularly in scenarios featuring long-term dependencies. Nevertheless, the success of neural networks, especially LSTMs, necessitates meticulous tuning and a larger volume of data. Recommendations include opting for ARIMA in cases where time series data manifests linearity and clear patterns, while for intricate patterns, nonlinearity, and extended dependencies, NN-based methods like LSTM might yield superior results. Simple methods like SMA and SES are proposed as foundational benchmarks, especially for datasets exhibiting straightforward patterns. Ultimately, the optimal approach is contingent on the specific attributes of the data and the forecasting objectives, emphasizing the need to experiment with various methods and assess their performance using relevant metrics on a validation dataset [20].

## CONCLUSIONS

Our study successfully demonstrated the development of a smart meter, showcasing the careful assessment and calibration of STPM32 and ADE7758 metering ICs. Calibration involved precise comparisons of register values with actual voltage and current readings from a reference meter, establishing accurate linear relationships. Time series analysis of appliance power consumption revealed distinct energy usage patterns, with the Sayona audio system being the most efficient and the Mika room heater consuming the most power. The research validated the accuracy of the smart meter by quantifying error metrics, including Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), for the ARIMA model predicting motor power consumption. Notably, the ARIMA model, with crucial coefficients like AR(1), MA(1), and the constant term, exhibited significant predictive capabilities, capturing dependencies in the time series data. The active power consumption of the motor was precisely determined, averaging 250.95 Watts, with daily and hourly consumption indicating efficient energy utilization. The time series plot further illustrated anticipated upper and lower boundaries around the mean power consumption, emphasizing the model's reliability. The motor's impressive daily energy consumption of approximately 6 kWh reinforces the effectiveness of the smart meter in monitoring and optimizing energy usage.

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## NOMENCLATURE

| | |
|---|---|
| ARIMA | Autoregressive integrated moving average |
| MAE | Mean Absolute Error |
| RMSE | Root Mean Squared Error |
| IoT | Internet of Things |
| EMS | Energy Management Systems |
| ANNS | Artificial Neural Networks |
| SVMs | Support Vector Machines |
| FL | Fuzzy Logic |
| GAs | Genetic Algorithms |
| STLF | Short-term load forecasting |
| MTLF | Medium-term load forecasting |
| LTLF | Long-term load forecasting |
| GSM | Global System for Mobile Communications |
| MCU | Micro-controller Unit |
| ADC | Analog-to-digital converters |
| MEMS | Micro-electromechanical Systems |
| PCB | Printed Circuit Board |
| SIM | Subscriber Identity Module |
| Wi-Fi | Wireless Fidelity |
| LEDs | Light-emitting Diodes |
| IC | Integrated Circuit |
| SPI | Serial Peripheral Interface |
| UART | Universal Asynchronous Receiver/Transmitter |
| AR | Autoregressive |
| MA | Moving Average |