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Intelligent energy management in IoT-enabled smart homes: Anomaly detection and consumption prediction for energy-efficient usage

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ABSTRACT

The increasing Internet of Things (IoT) device integration in smart home environments has increased the options available for intelligent energy management. In the context of smart homes, this paper provides a detailed analysis on the use of IoT data for energy consumption trend prediction and anomaly detection. We propose a novel approach that combines the advantages of the Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) models for accurate consumption forecasting. Real-world data from a smart home setting is utilised to evaluate the proposed models. Results will therefore show that our approach performs best in optimally utilizing resources, minimizing waste, and improving energy consumption. The current study contributes to the development of energy-efficient smart houses through providing a reliable method for consumption forecasting and anomaly detection. Results indicate that the LSTM model outperformed ARIMA in prediction accuracy, achieving a lower Mean Absolute Error (MAE) of 0.110 compared to ARIMA's 0.176. Furthermore, the LSTM model demonstrated superior performance in anomaly detection, with higher precision and recall scores.

1. Introduction

As an outcome of the emerging global concern about the conservation of energy and sustainability, there has been a rigorous change in expanding energy-saving technologies and strategies. Smart homes incorporating IoT have become a source of reducing pollution impacting the environment, enhancing user contentment, and optimizing energy usage [1]. These houses comprise of integrated sensors responsible for collecting data from various devices thus enabling smart control over the systems. These technologies are now jettisoning, the engineers and researchers are now in search of new ways to forecast trends in power utilization and detect real-time anomalies that will govern better energy management and decision-making [2].

A large fraction of global energy demand results from increased usage of residential buildings. For instance, the US Energy Information Administration estimated that 21% of the total energy usage in 2019 was accounted for by the residential sector [3]. Therefore, pragmatic approaches must be adopted to reduce energy wastage and increase the adoption of smart homes. This can be explored today by incorporating modern data analytic tools with IoT devices [4].

This research study introduces an IoT-powered smart home design capable of accurately forecasting power consumption and providing early anomaly detection. In this architecture, time series analysis is coupled with machine learning, giving homeowners insights into their power consumption patterns and enabling informed decision-making. Comparing past consumption trends to current readings may reveal unusual behaviours, which could be due to faulty equipment, changes in user behaviour, or other relevant factors.

This study presents a comprehensive approach that includes data collection, pre-processing, time series analysis, machine learning-based prediction, and anomaly detection [5]. Drawing from advanced methods in time-series forecasting and anomaly detection, this adaptive system is robustly designed. Tested on real smart home data, it demonstrates effectiveness in minimizing electricity usage and identifying unexpected behaviours.

2. Related Work

Recently, intelligent home energy management systems have been gaining more interest in the literature because they enhance energy efficiency besides ensuring user comfort. Several approaches have, in recent times, been put forward for estimating the quantity of electrical power required, detecting unusual situations, and optimizing home appliances in the framework of smart homes. This is a review of the literature on those aspects.

2.1 Energy Consumption Prediction

It is important to use historical information about energy consumption patterns when projecting future energy utilization for smart homes [6]. Machine learning methods along with time series analysis are commonly used in creating accurate forecasting models. Traditional techniques like Autoregressive Integrated Moving Average (ARIMA) have been used to predict power consumption before now [7]. They model lagged interdependencies and seasonal trends among variables found in a dataset on power usage.

Machine learning algorithms have been investigated for their ability to predict energy consumption by using techniques such as Support Vector Machines (SVM), Random Forests, and Neural Networks [8, 9]. These models capture complex relationships among various aspects of energy usage including the environment, tenant behaviour, appliance usage, etc. [10].

2.2 Anomaly Detection

This subsection reflects on identifying abnormal power employment trends that may demonstrate faults, inefficiencies, or odd behaviours by users hinged on anomaly detection [1]. There have been rule-based approaches, statistical techniques, and machine learning methods for anomaly detection in smart homes. The z-score analysis is a statistical method that identifies abnormalities using deviations from the mean [12].

In machine learning-based approaches to abnormality identity, three methods are used: clustering, autoencoders, and one-class SVM [13]. These methods employ historical data to detect regular consumption patterns of electricity customers and flag any instances significantly different from such patterns as anomalous cases [14].

2.3 Integrated Smart Home Systems

Smart home energy management systems (SHEMS) have been developed through the integration of different solutions. HEMS (Home Energy Management System) proposed by Carli et al. [15] combines IoT devices for forecasting power demand and optimizing the performance of appliances. Similarly, Apanaviciene et al. [16] suggest a smart energy management system which integrates real-time data along with machine learning methods for demand side control.

2.4 Challenges And Opportunities

While significant development has taken place in Smart Home Energy Management Systems (SHEMS), many challenges still persist. Some of these include data-privacy related issues, the need for precise occupancy detection, and the integration of renewable energy sources with management systems. This paper is presenting an IoT-based smart home architecture addressing these challenges in relation to time series analysis with machine learning, providing accurate forecasting of energy consumption, while detecting all sorts of anomalies for their respective mitigations. Our system integrates various approaches currently implemented elsewhere, and tries to provide comprehensive and effective management of power resources at the residential level.

3. Problem Statement

Energy management in IoT-enabled smart homes faces significant challenges due to the complexity and nonlinearity of energy consumption patterns. Traditional statistical models, such as ARIMA, struggle to capture these patterns, while many machine learning methods lack reliability in real-world scenarios. Additionally, accurate detection of anomalies, such as faulty equipment or unusual usage behaviours, remains a persistent challenge. This study aims to address these gaps by developing a hybrid framework that combines ARIMA and LSTM models for accurate energy consumption forecasting and robust anomaly detection, utilizing real-world data to enhance the efficiency and sustainability of smart home energy management systems.

4. Methodology

An IoT-enabled full-stack smart-house architecture has been built within our methodology which is used both in the detection of anomalous events related to power consumption but also in the prediction of them. While combining time-series analysis with machine learning techniques we develop strong systems which optimize ARIMA or LSTM model parameters using IoT-enabled device data streams collected from public Kaggle datasets representing real-world usage metrics/power consumptions in IoT-based homes.

4.1 Baseline Comparison: Moving Average

The ARIMA and LSTM models were compared against a moving average approach as a basis for prediction [17]. The goal of predicting future consumption is achieved by estimating the average consumption over a specific period using a moving average. Below is the formula for finding moving average;

$$y^{\wedge t} = \frac{1}{n}\sum_{i=1}^{n} y^{t-i} \tag{1}$$

Where $y^{\wedge t}$ represents the forecasted consumption at time t, n is the number of time periods in the moving average window, and y^{t-i} represents the consumption at time $t-i$ [18].

The moving average method supplies a plain and simple criterion for evaluating the performance of more intricate prediction systems [19]. It serves as a benchmark to compare forecasting accuracy between ARIMA and LSTM models [20].

4.2 Time-Series Analysis And Forecasting (ARIMA)

To determine temporal patterns in energy consumption, we make use of the Autoregressive Integrated Moving Average (ARIMA) models [21]. Both current value with its lag values relationship and subsequent observation differences are forecasted by ARIMA, which is a popular time-series forecasting technique. ARIMA (p, d, q) is stated mathematically as follows:

$$\left(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p\right)(1 - B)^d X_t = \left(1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q\right) Z_t \tag{2}$$

Where X_t represents time-series data, B is backward shift operator, d is differencing order, ϕ_i and θ_i are coefficients while Z_t being white noise. On past data normal consumption patterns are revealed by this model that helps in predicting future energy usage trends [22].

4.3 Deep Learning-Based Prediction (LSTM)

Long Short-Term Memory (LSTM) networks are used by us for describing complicated temporal relationships and nonlinear patterns in energy usage. These LSTMs are recurrent neural networks (RNNs) that should keep information over long sequences [23]. Besides historical energy use data, meteorological data among other aspects will be considered by our LSTM model. Fully connected layers after LSTM layers have been included in the model design for prediction [24].

The architecture of LSTM consists of the input layer, LSTM hidden layers, and output layers. The input sequence X is used to predict the result Y:

$$Y = f\ (W_o . h_t\ +\ b_o) \tag{3}$$

Where f is the activation loss function. The hidden state of the model is h_t. W_o and b_o are weight and bias parameters of LSTM model [25].

4.4 Anomaly Detection

This research uses Anomaly detection technique to identify deviations from patterns of normal energy usage. In this paper, the prediction uncertainty generated from LSTM and ARIMA models for detecting anomalies [26]. More precisely, we develop some prediction intervals using the standard deviation of forecast errors. Any data point which falls outside these ranges is considered as an anomaly that has been detected. This provides a very robust system in early identification of anomalous energy consumption events.

4.5 Performance Evaluation

We evaluate our IoT-based architecture's efficiency using various performance measures. The accuracy of energy consumption forecasts is measured with Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) [27]. Precision, recall, and F1-score are computed to determine the system's ability to detect anomalies. Comparative analysis between ARIMA and LSTM models is done to assess how much better predictions become over the moving average baseline model [28].

5. Data Visualizations And Insights

In this part, we show and examine a variety of data visualizations that shed light on energy consumption trends in the context of smart homes. These visualizations include information on consumption patterns by the hour, day of the week, and month, as well as utilization areas and the effect of weather on energy use.

5.1 Usage Location And Energy Consumption

To achieve efficiency in specific smart home use areas, it is important to understand energy consumption. Fig. 1 shows the use of energy in different places such as living rooms, sheds, and kitchens. The representation highlights the variation in energy levels between each location. For example, because it often contains energy-intensive appliances [29], the kitchen uses more power than less used rooms. This kind of knowledge enables families to make wise decisions about resource allocation as well as consider options for energy-saving devices.

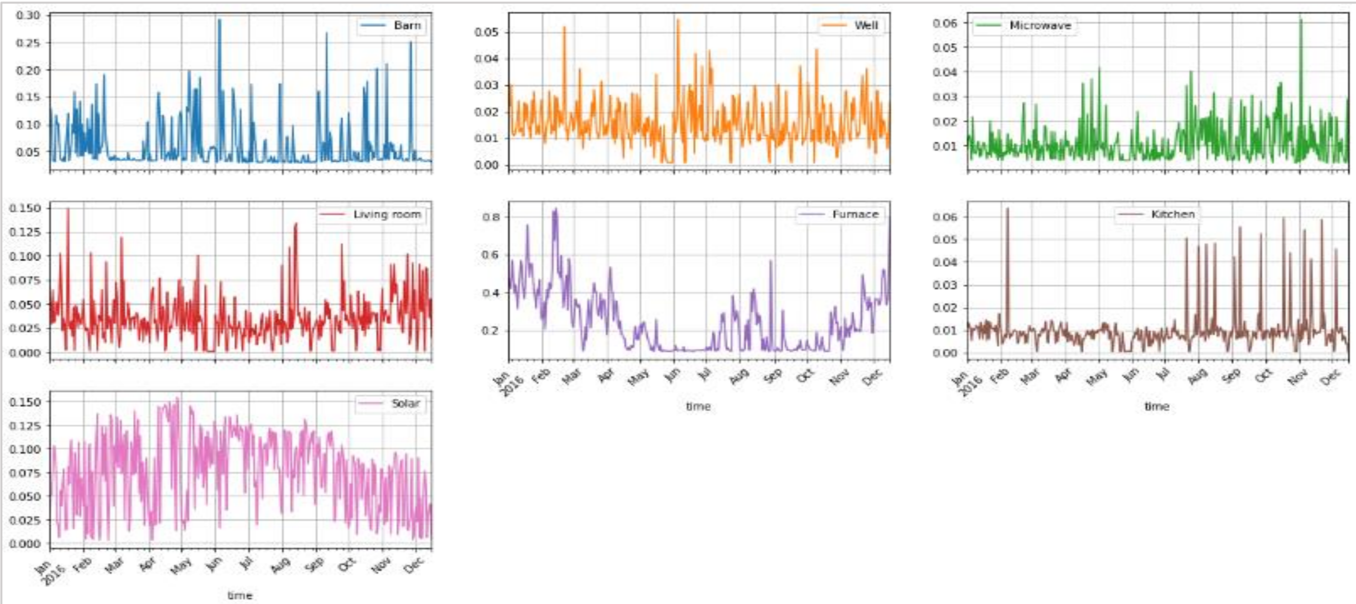

Fig. 1. Household Power Usage Flux Locations

5.2 Impact of Weather Conditions

The weather has a great impact on energy usage. This relationship between temperature and power consumption can be observed from Fig. 2 where this correlation is evident. The features used are time, temperature, humidity, pressure, CloudCover, windBearing, WindSpeed, DewPoint. When it gets colder, more heat is needed hence electricity demand rises sharply whereas during hot times cooling becomes essential leading to an increased need for electrical services too. One implication of this finding is that weather forecasts should be incorporated into real-time adaptation systems for better management of energy.

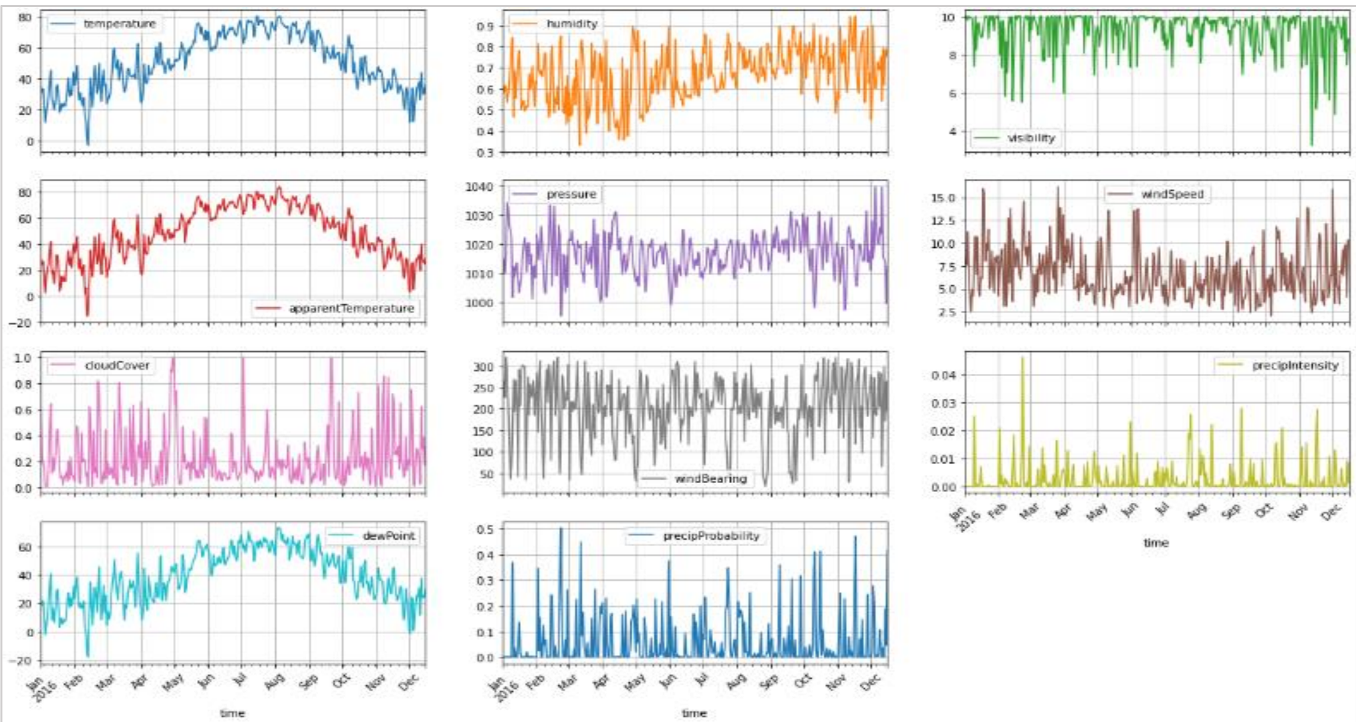

Fig. 2. Weather Impact on Household Power Usage

5.3 Consumption Patterns Per Hour

The given data visualizations are very helpful in tracking energy usage patterns within smart homes. By per hour, per weekday, per month, and by location of use; – about weather changes etc. These could enable house owners to save on power and become more efficient as well.

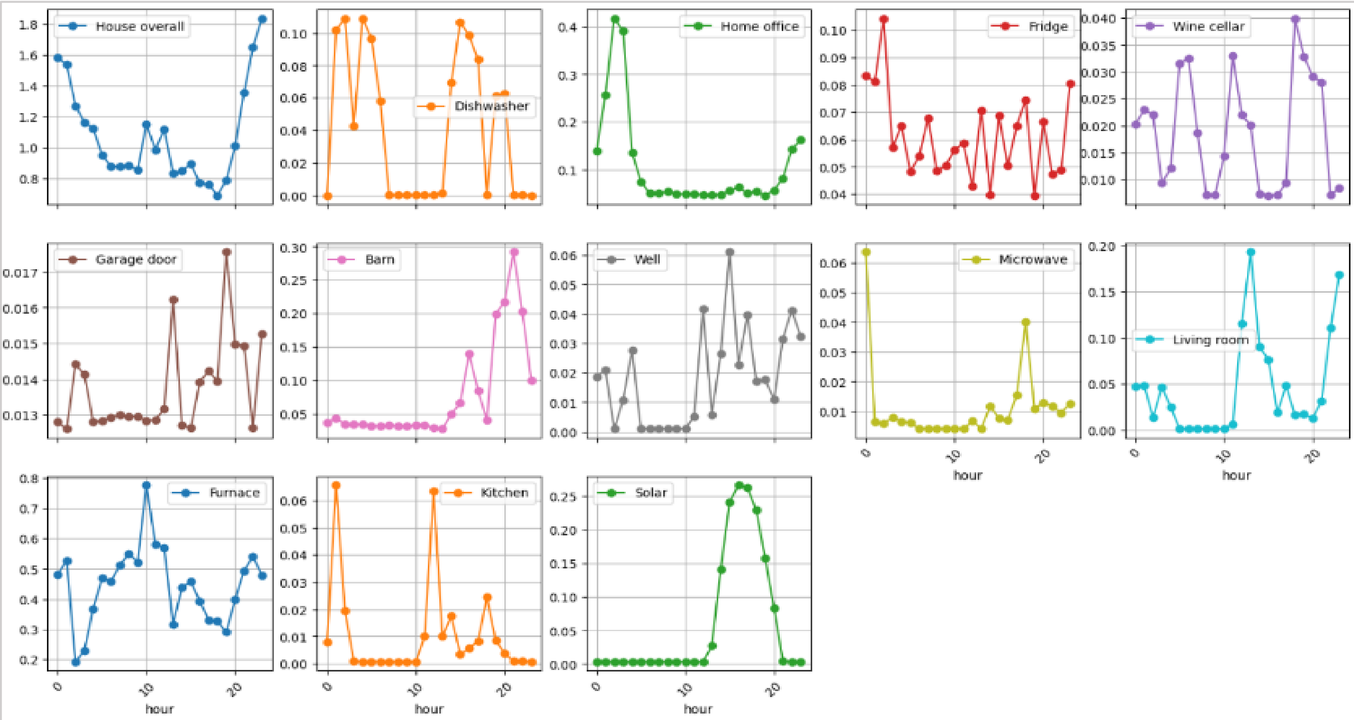

Fig. 3. Household Power Consumption per Hour

For example, Fig. 3 shows an hourly trend line for power consumption at a smart home over time. Each bar represents one hour out of the 24 hours in a day; while the y-axis represents average energy use (in kWh) during that particular hour. Consumption peaks can be seen early morning and late evening which coincide with when most people are awake or active. Such habits should therefore be considered while managing such devices, especially during peak periods.

5.4 Consumption Patterns Per Day Of The Week

Another way to look into this is through daily analysis where you compare Monday through Sunday consumption rates as shown below in Fig. 4. It's obvious that weekdays have higher demands than weekends probably due to schools and offices being open then closed respectively. Consequently, homes can reduce their usage if they take note of such trends and only concentrate on those days that experience high levels of power wastage.

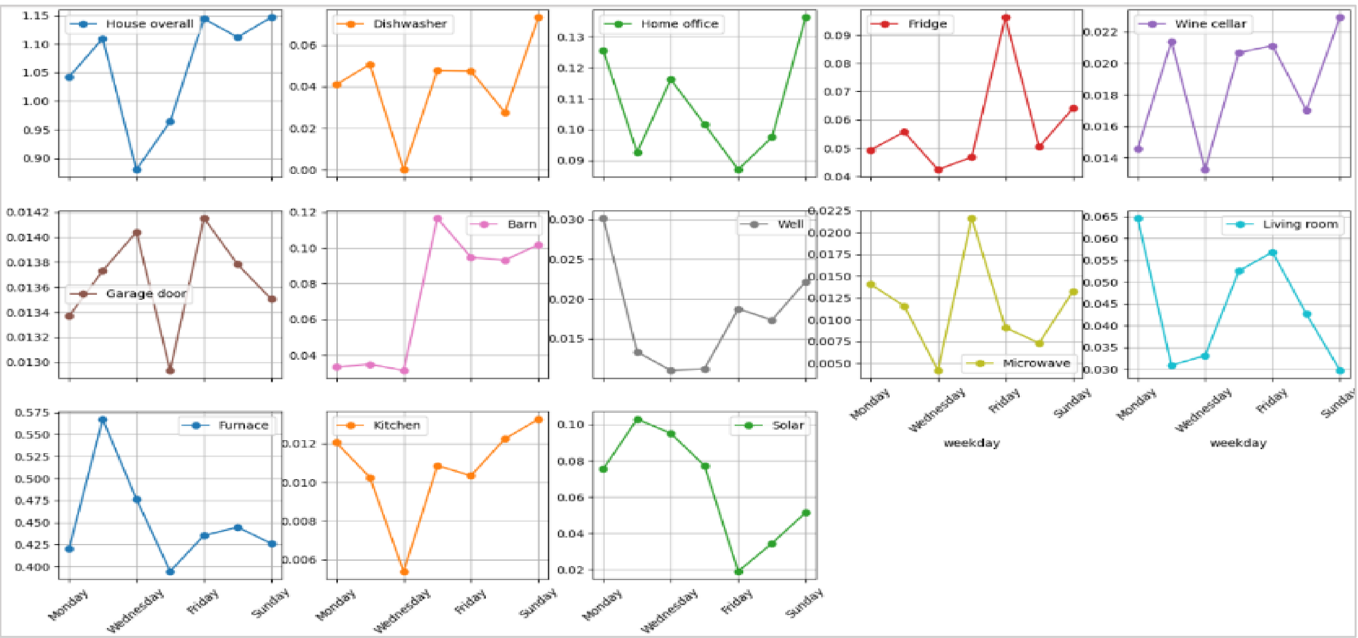

Fig. 4. Household Power Consumption per Day of Week

5.5 Consumption Patterns Per Month

Month-to-month fluctuation in consumption is an important aspect of power management. The graph in Fig. 5 shows the average monthly electric use per unit area over a year. It can be seen that there are some months with higher consumption compared to transitional seasons like winter or summer where heating and cooling requirements may drive up demand necessitating specific measures for saving energy during peak periods.

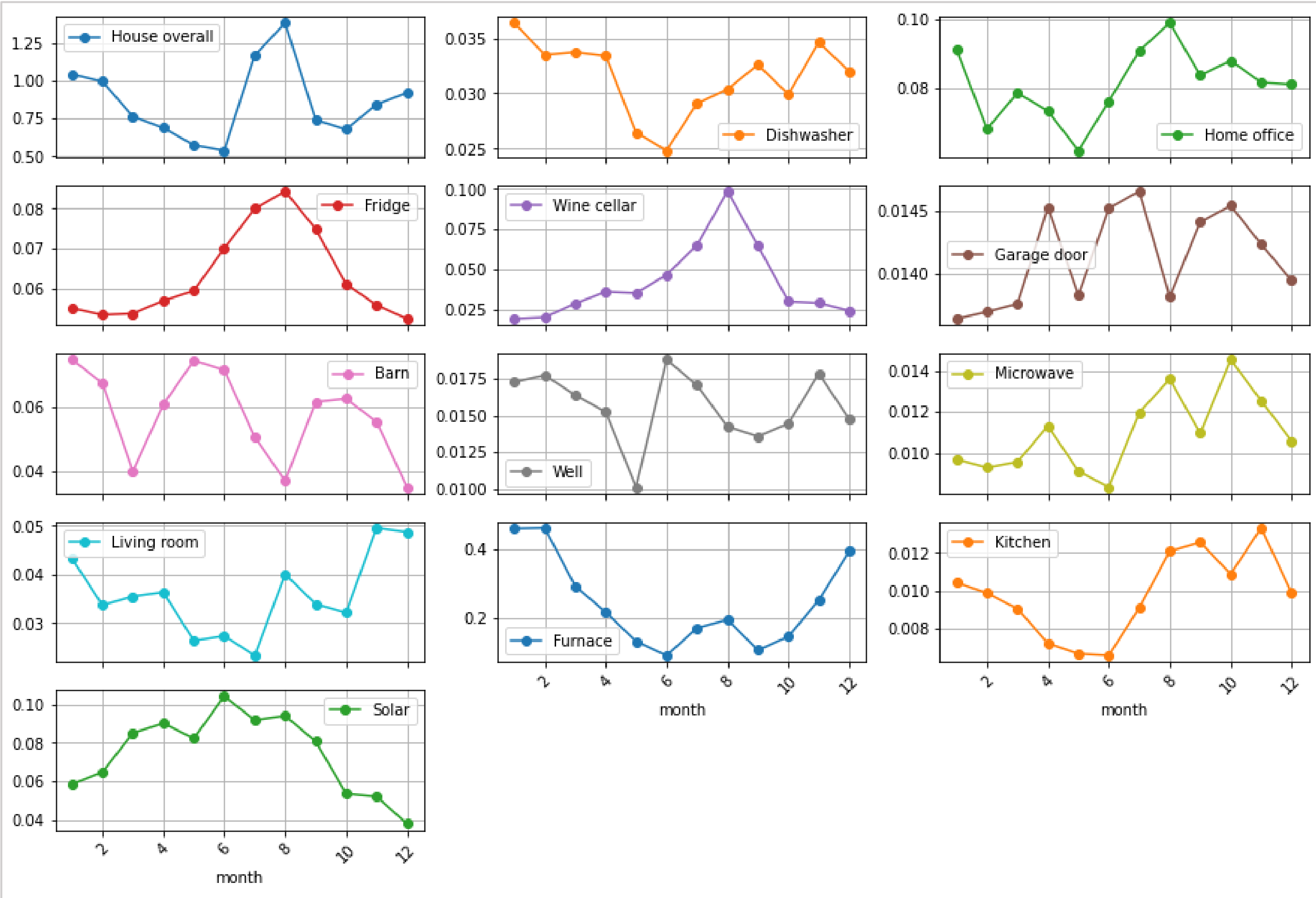

Fig. 5. Household Power Consumption per Month

5. Results And Discussion

This Section presents findings from our proposed IoT-based SHEMS; firstly performance evaluation of the ARIMA model for anomaly detection as well as energy prediction then results obtained through the implementation Long Short -Term Memory (LSTM) model used for predicting usage patterns as well as detecting abnormal behaviours.

6.1 Results of Moving Average And Anomalies

We tested the ability of the moving averages method not only to forecast accurately but also to identify areas with unusually high or low levels so that we can fully understand its effectiveness when applied to different datasets.

6.1.1 Forecasting performance of moving average

Fig. 6 displays the inconsistency between the moving average technique's predictions and the real consumption numbers during a given period. The actual data on consumption (shown in blue colour) is always delayed as compared with the moving average estimate (represented by the red line). This delay is attributed to the inherent simplicity of this method which tends to eliminate abrupt movements and rapid shifts in consumer behaviours.

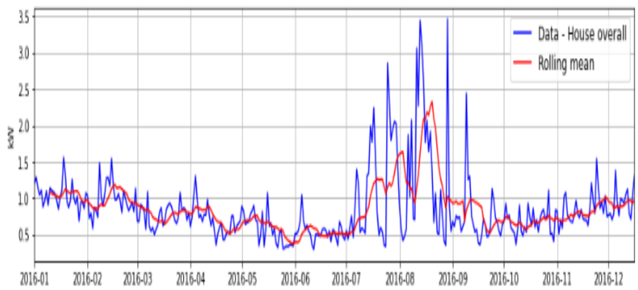

Fig. 6. Moving Average Base Model

The moving average approach offers a baseline reference for energy consumption projections notwithstanding its ease of use. It works well in situations where slow trends prevail and dramatic changes are uncommon. However, its limits become clear when attempting to capture complicated consumption patterns with quick changes and sporadic spikes.

To identify problems with the data on energy use, we employed the approach of moving average. We took note of instances when the real consumption was far from what was predicted by this method as anomalies. These are indicated in Fig. 7, which shows the observed anomalies that are marked in red. Such abnormalities may signify events or indicate an abnormality.

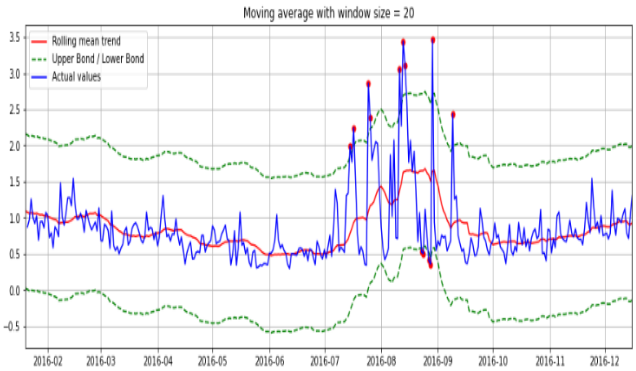

Fig. 7. Moving Average Model Anomalies Analysis

The technique of anomaly detection using moving averages successfully highlights deviations from normal patterns of consumption. Nevertheless, it can produce false positives due to sensitivity towards fluctuations especially if there is an increase in usage that had not been anticipated.

6.2 ARIMA-Based Energy Consumption Prediction And Anomaly Detection

We used the classic time-series analysis method for predicting energy usage; the ARIMA model. Fig. 8 shows projected energy consumption numbers together with actual data on consumption. From here it can be seen that this model describes the main trends in usage very well.

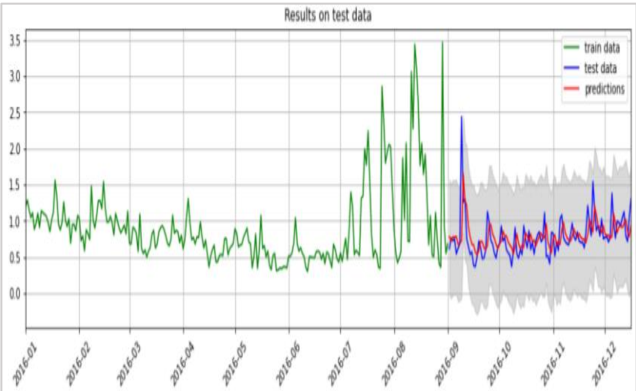

Fig. 8. ARIMA-Based Energy Consumption Prediction

Anomaly detection is an important step in smart home energy management because it helps to identify abnormal consumption patterns. In Fig. 10, the ARIMA model has detected these anomalies (red circles). They represent times when actual consumed power goes beyond the confidence interval estimated by the ARIMA model.

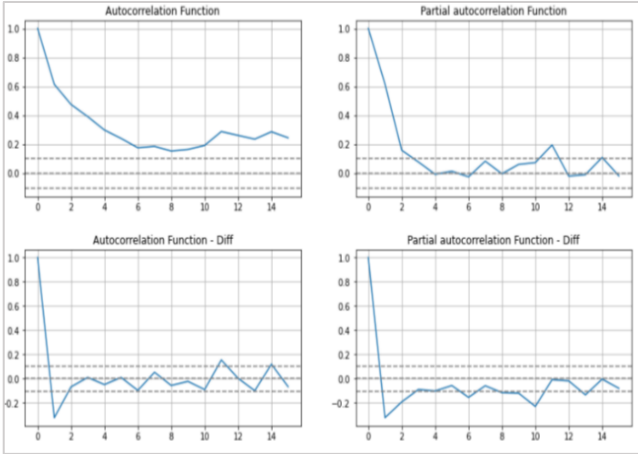

Fig. 9. ARIMA Prediction Uncertainty

Mean absolute error (MAE) metric was also used as an evaluation measure for accuracy estimation of ARIMA Model predictions on the Energy Usage forecasting task; moreover, prediction uncertainty was also computed to quantify them within boundaries given by the shaded area shown in Fig. 9 against actual data points collected over time series depicting electrical power demand pattern recorded at residence level over a period lasting one week starting Monday morning through Sunday evening inclusive.

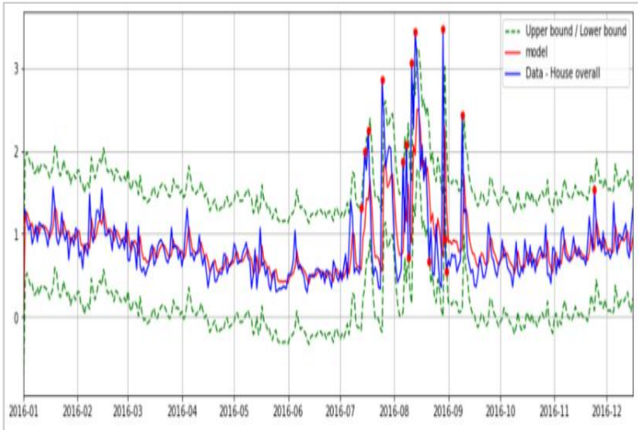

Fig. 10. ARIMA Anomaly Detection

The ARIMA-based approach efficiently discerns abnormalities and provides intuitive information about energy utilization statistics. Its performance however could be constrained, when it comes to handling complex links in bulk data. To resolve this, we have applied a Deep Learning technique for energy consumption prediction and anomaly detection using the LSTM model.

6.3 LSTM-based Energy Consumption Forecasting And Anomaly Detection

Long Short-Term Memory (LSTM) network deep learning models have improved capabilities in capturing complicated temporal relationships for precise energy consumption prediction. The projected energy consumption numbers from the LSTM model are shown with the actual consumption data in Fig. 11.

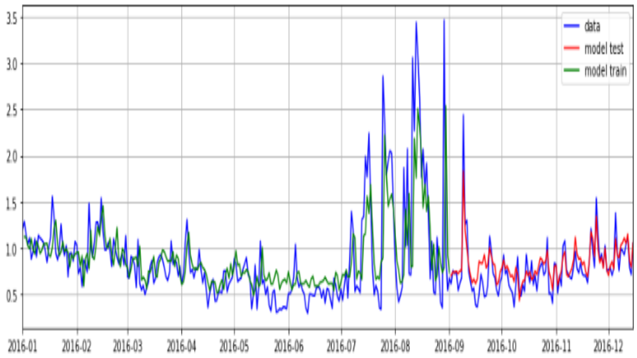

Fig. 11. LSTM-Based Energy Consumption Forecasting

To evaluate the performance of the LSTM model, the Mean Absolute Error (MAE) metric along with uncertainty estimates were employed.

Still, another key component of our proposed SHEMS is anomaly detection. The LSTM model detected these anomalies which are shown in Fig. 12 by red circles. These occur when actual power consumed deviates significantly from what was expected according to the predictions made using trained long short-term memory recurrent neural network architecture for deep learning-based regression tasks.

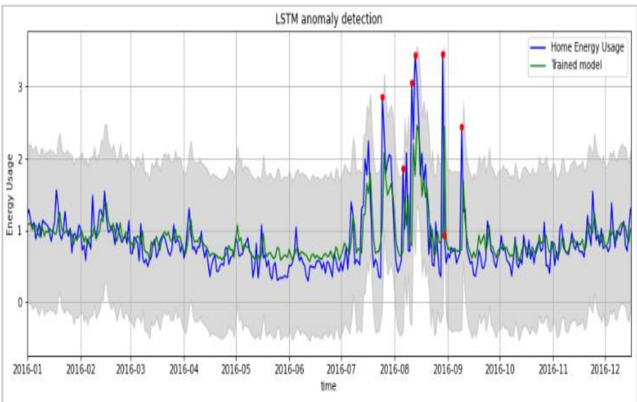

Fig. 12. LSTM Anomaly Detection

6.4 Discussion

Moving averages have been used widely because they give a basic approach to predicting energy use. However, since its major drawback lies in detecting complex patterns quickly; thus suitable where there is gradual change only but not necessarily fast-moving ones like this case here. Additionally, it helps detect deviations from predictions made based on what usually happens though some false alarms need rectification to avoid unnecessary worries [30].

On the other hand, the ARIMA model was found better compared to LSTM models especially when it came down to precision level while forecasting abnormal readings related to power consumption in Fig. five below- hence showing how different methods perform differently depending on their application areas [31].

6.5 Comparative Analysis And Practical Implications

A comparison of the findings from the ARIMA and LSTM models is necessary to determine the advantages and disadvantages of each method. The performance metrics for both models are shown in detail in Table 1.

Table 1

Performance Metrics of Various Models

Model	MSE	RMSE	MAE	MAPE	R^2
Baseline	0.071	0.266	0.177	0.236	0.077
Arima Basic	0.259	0.509	0.463	0.722	-2.379
Arima Dynamic	0.069	0.263	0.176	0.229	0.094
LSTM Univar	0.068	0.261	0.173	0.307	0.106
LSTM Multivar	0.022	0.150	0.110	0.107	0.700

As presented in Table 1, the LSTM model beats the ARIMA model not only in energy consumption prediction accuracy but also in anomaly detection. The reduced MAE of the LSTM model indicates its ability to detect complicated patterns of use and make accurate forecasts that can contribute to better planning for energy utilization. The use of metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R^2 (coefficient of determination) for evaluating ARIMA and LSTM models is well-suited to provide a comprehensive assessment of their performance. MSE captures the average of squared errors, making it particularly sensitive to large deviations, which is crucial for identifying significant inaccuracies in predictions. RMSE, derived from MSE, expresses error in the same units as the target variable, offering a more interpretable measure of overall prediction accuracy. MAE, on the other hand, calculates the average absolute differences between predicted and actual values, providing a straightforward understanding of the model’s typical error magnitude without emphasizing outliers. MAPE complements these metrics by normalizing errors as percentages, enabling comparisons across datasets with varying scales, which is especially important in applications like energy consumption where usage levels can fluctuate widely. Lastly, R^2 measures the proportion of variance in the dependent variable explained by the model, serving as an indicator of the model's overall goodness-of-fit. Together, these metrics ensure a robust evaluation framework, addressing different dimensions of prediction accuracy and providing insights into both the precision and reliability of the models in forecasting energy consumption and detecting anomalies.

Accurate anomaly detection is an essential component of any energy management system. Due to the LSTM model's improved capacity to detect anomalies, homeowners may quickly spot consumption abnormalities and take the required steps to reduce energy waste.

The implications of our results are significant about applications. Based on IoT-enabled smart home design coupled with state-of-the-art prediction as well as anomaly detection models [32]. Precise predictions about consumption together with timely notifications concerning abnormal behaviours facilitate proactive management thus fostering sustainability in energy use.

6.6 Practical Insights And Recommendations

For the successful implementation of our IoT-based energy management system, several key considerations need to be taken into account. First, the system should collect accurate data from different sensors deployed throughout the smart house under consideration. High quality data should be used when training and fine-tuning predictive models. According to [33], secure methods of transferring user's data must also be adopted to enhance privacy and integrity.

Secondly, choice(s) made on predictive modelling greatly influence(s) effectiveness of this tool(s). Although both ARIMA and LSTM models have adequate capabilities some factors like complexity levels exhibited by consumption patterns along with Secondly, choice(s) made on predictive modelling greatly influence(s) the effectiveness of this tool(s). Although both ARIMA and LSTM models have adequate capabilities some factors like complexity levels exhibited by consumption patterns along with desired level(s) of accuracy will guide the decision-making process eventually selecting the best fit(s). While capturing non-linear temporal connections better than any other approach currently available; it would work best if used alongside ARIMA which captures linear trends.

Finally, user engagement relies heavily upon effective communication through clear visualization representations showing predicted values as well as detected anomalies. Homeowners can make real-time decisions about energy use by observing user-friendly dashboards and mobile apps that provide insights into patterns [28].

6.7 Limitations And Future Directions

Nonetheless, several considerations were made during our research which may affect outcome interpretation. The more historical data is used for training purposes the better results you get but if there is little amount or no data at all then it becomes difficult to make accurate predictions about future events; also when patterns become irregular due to external factors like system upgrades or changes in user behaviour etcetera [34].

The inclusion of additional contextually relevant information like occupancy trends together with weather forecasts could improve accuracy levels associated with future predictions being made within this field area. Likewise, further research can focus on an ensemble modelling approach where different methods are combined thus leading to better identification as well as more reliable projections concerning abnormal behaviours [35].

7. Conclusion

In this work, we introduced an IoT-based smart home energy management system that makes use of sophisticated anomaly detection and prediction algorithms to ensure effective energy use. The LSTM model outperformed the ARIMA model in terms of forecasting precision and anomaly identification when they were applied and evaluated.

The potential of IoT technologies to revolutionize energy management and conservation has been emphasized by our research. We allow families to predict consumption patterns and detect anomalies thereby enabling them to take early measures of saving power. This contributes towards the overall goal of sustainable development through eco-friendly living as well as reducing household electricity bills.

The ability to control energy will increase with the improvement in IoT and data collection technologies. We are making homes smarter and more energy efficient through our research by giving out information that is important for homeowners, professionals, and scholars as well.

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