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Intelligent Household Load Identification Using Multilevel Random Forest on Smart Meters

Israa Badr Al-Mashhadani [1]*, Waleed Khaled [2]

[1] Department of Computer Engineering, College of Engineering, Al-Nahrain University, Jadriyah, Baghdad, 10001, Iraq
[2] Department of Medical Instruments Engineering Techniques, Al-Farhadi University, Jadriyah Bridge, Baghdad, 10001, Iraq
*Corresponding Author: Israa Badr Al-Mashhadani

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ABSTRACT: A load identification approach for residential intelligent meters using a random forest (RF) algorithm is employed to guarantee the secure and cost-effective functioning of the electricity grid. In this study, the load data from a smart meter in a home was pre-processed to remove any gaps, noise, or inconsistencies before making any predictions by using the random forest method. The power quality (PQ) features, current features, and Voltage-Current (V-I features), as well as the forecast findings and mathematical tools were used to recognise the load. Using these tools, the household intelligent meters utilising the random forest algorithm, features, harmonic characteristics, and instantaneous characteristics were extracted to form the load characteristics, and the objective function of load identification was generated based on a set of features. The findings of this comparative study demonstrate that employing this technique can reduce identification errors and boost productivity by a full two seconds. The proposed approach, based on a random forest technique, improved home power savings rate by 99.2% and the load management efficiency by 98.6%.

Keywords: Random Forest Algorithm, Household Load, Smart Meter, Pre-processing Techniques

1. INTRODUCTION

In recent years, the importance of smart meters to the advanced metering infrastructure (AMI) of contemporary utility systems has come into sharp focus. Power companies and homeowners alike can benefit from the real-time information on electricity consumption provided by these meters. However, in order to utilise smart meters to their full potential, there is a need to pinpoint the specific gadgets and electronics that consume power. Demand-side management, energy conservation, and adding energy from renewable sources to the grid are easy to position once the loads that compose these systems are correctly identified. A load identification approach for residential intelligent meters that uses machine learning techniques is shown [1]. This approach breaks down overall energy use into data that is specific to appliances. Due to the dynamic nature of home energy consumption patterns, load identification is a complex process, as there is limited accuracy with which rule-based or mathematical techniques may discriminate between various home appliances. However, machine learning methods have demonstrated impressive promise in evaluating and extracting useful information from massive energy datasets. By training on labelled data, machine learning algorithms can learn the unique electrical features and processes that accompany each appliance. Therefore, it is possible to identify individual loads based on the power they use [2].

Precise identification and control of domestic electrical loads play a key role in minimising the use of energy and boosting the effectiveness of electrical systems in the age of smart homes and energy conservation. In this work, we employed cutting-edge machine learning methods, in particular Multilevel Random Forest, to data gathered from residential smart meters in order to meet this pressing demand. As more and more homes are installing smart meters, the exact amount of energy used by each appliance or equipment in the home in near real-time can be determined. However, the segmentation of this data to correctly identify specific loads, such as lights, HVAC, and appliances, poses a significant difficulty. Nonetheless, to address this issue, an advanced ensemble learning process known as Random Forest can be used. The non-intrusive monitoring and identification of loads in smart grid load monitoring systems has garnered significant attention in this field; however, current studies only consider the load identification accuracy rather than the efficiency of data sampling, the uniqueness of load abstracted representation of features, or the trustworthiness of the load identification model.

Imperative aspects of smart grid management of energy include accurate energy consumption forecasts for smart buildings, demand response strategies, and the establishment of dispersed generating equipment. Energy consumption forecasting at various transmission and distribution network levels has previously been approached from a variety of angles. Electric demand forecasting for a single energy consumer, as opposed to the aggregated load of several consumers, is difficult due to natural uncertainty and unpredictability. According to [3] this research focuses on the possibility of smart meters fitting into the rapidly developing energy market made possible by digitalisation and IoT.

 *Corresponding author: israa.b.al-mashhadani@nahrainuniv.edu.iq

The emergence of 5G technology has made it easier for smart grid devices and stakeholders to communicate with one another. A unique event-driven adaptive-rate sampling technique, which successfully compresses real-time data to improve data collecting and processing, was suggested. In order to identify loads, support vector machine methods were used to extract useful information from power consumption trends. The outcomes depicted a 3.7x reduction in data size, processing speedups, and a 96% improvement in classification precision. The data collected over the 5G network can be safely stored in the cloud for additional examination and utilisation in making decisions. In another study by S. Shi et.al., the algorithm based on decision trees was used to offer a load detection approach for residential smart meters [4]. In order to forecast load data after pre-processing, the study addressed issues including missing, noisy, and inconsistent data using the decision tree technique. PQ, present, V-I, harmonic, and instantaneous features were then employed as mathematical inputs to extract the load characteristics. A load identification objective function was also built using these features. Compared to other approaches, this method decreased load error rates, boosted recognition efficiency, and identified objects in about 1.5 seconds. The proposed solution helped in guaranteeing that the electricity system is running efficiently and safely. Another study created a method for identifying appliances and classifying ADLs in the home by leveraging information from smart meters [5]. It employed a difficult classification challenge to determine the appliances that belonged to a given home by breaking down a main's electricity reading into its component parts. Deep learning has also become the preferred method for categorisation in high-demand areas, such as processing images and recognition of speech, due to the recent advancements in the discipline. For the purpose of identifying common household electrical equipment from typical smart meter data, the paper provided a deep learning technique that utilises multilayer, feedforward neural networks. Utilising open-source smart meter data sets, the efficacy of this method was examined and verified. The discovered home electronics were then linked to several Activity of Daily Living (ADL) classifiers. The resultant ADL classifier showed several uses in the energy sector and beyond, including providing data on the choices of household inhabitants [5]. Using an advanced deep-learning recurrent neural network that includes Long Short-Term Memory (LSTM) modules that are adaptable to each aggregate load and individualised household load, this research investigated the forecasting problem. In order to test the efficacy of the suggested LSTM deep learning approach, data from individual smart meters in homes and aggregated electricity demand information from publicly available sources were used. Several standard forecasting techniques were also employed to evaluate the proposed model. The results depicted that the recommended LSTM model was superior to other prediction approaches when applied to forecasting at the household level [6–9]. These research delved into the feasibility of using low-cost, inconspicuous smart-home sensors in environmental care tools to help people in their everyday lives and reduce their energy bills. The research focused on using methods of deep learning and machine learning on data from activity sensors in the home. To facilitate user profile and energy optimisation, it is necessary to detect and foresee actions, such as appliance use and electricity use. Data from position sensors, door sensors, cell phones, and smart meters were a few of the sources analysed in the study. The work was broken down into four primary chapters, each of which contributed to a distinct area of machine learning and the use of deep learning approaches. Non-intrusive load monitoring (NILM) algorithms to detect individual electrical loads and categorise appliances, machine learning methods for recognising activities, and dimensionality reduction techniques were also presented. The results were meant to provide a basis for advanced technologies that contribute to energy-saving programs by effectively using available resources [10–12].

Therefore, the proposed solution improved upon prior work in load recognition utilising machine learning to create a dependable and productive strategy for residential smart meters. A supervised learning system was employed for this study, where a random forest algorithm was trained using a labelled dataset for training appliance power usage data. The input model was fed information from the smart meter readings, including voltage, real power, exists, and reactive power. Our goal was to improve the reliability of load recognition by employing features such as engineering and technique selection to capture the unique properties of various loads. Extensive tests were run on a real data set obtained from several household smart meters to observe the manner in which the load recognition algorithm performed in practice. In this case, it meant evaluating the random forest algorithm for its ability to correctly detect individual loads. Metrics including accuracy, recall, precision, and F1 score were used to assess whether the model could detect and categorise various home appliances. The tests demonstrated the usefulness and promise of random forest in load recognition for residential smart meters, which may lead to more efficient utilisation of energy and demand-side optimisation practices. The key contributions of this study are as follows:

- Machine learning techniques were employed to develop a load detection tool for residential smart meters. Specifically, this was done for the creation of a supervised learning architecture and the training of a random forest model using a labelled dataset of appliance power usage data. The goal was to assess how well a suggested random forest broke down overall energy usage into details about specific appliances.
- The performance of the suggested load detection system was shown in real-world settings along with its benefits. As part of this process, the data was collected from a sample of household smart meters to conduct trials and assessments. In order to facilitate demand-side management, energy saving, and the incorporation of energy from renewable sources into the grid, it is essential to reliably identify individual appliances, as will be shown using a random forest-based load classification algorithm.

- The effectiveness of different algorithms was analysed and compared using machine learning to identify home loads in smart meters. The goal was to evaluate the possibility of distinguishing and dividing appliances into categories according to their energy needs. The efficacy of these algorithms was measured and compared using evaluation measures such as F1 score, accuracy, recall, and precision.

This study is laid out as follows. Section 1 presents the related works on household load identification using machine learning on smart meters. The proposed methodology is detailed in Section 2. Section 3 shows the results and discussions on intelligent household load identification. Finally, the conclusion and future works of this study are presented in Section 4.

2. METHOD OF INTELLIGENT HOUSEHOLD LOAD IDENTIFICATION

The suggested approach employs the algorithm for random forests to provide a load detection system for homes with smart meters. Data from smart meters was used to precisely detect and categorise the various electrical loads in a home. The algorithm for random forests involves a machine-learning method to make predictions based on the output of several individual decision trees. As part of load recognition, students may learn to seek patterns and traits in the data from intelligent meters regarding how much energy is being used before sorting the data into groups based on the type of load it originates from. Several stages are involved in creating the load identification system. In the first step, data is gathered from home intelligent meters, and readings of energy usage are included in this dataset regularly, along with other relevant information, including time of day, weather, and occupancy levels. The next step involves pre-processing the dataset to account for missing information, thereby standardising the features, and eliminating anomalies. Once the data has been cleaned and prepared, it is divided into a training set and a test set. The training set fed the random forest algorithm by utilising the input characteristics, such as energy consumption figures and load labels, to learn. The random forest method acquired knowledge regarding the associations between the input characteristics and the load labels during the training phase. Numerous groups of data and features were considered while building each of the many decision trees, and the random element in the method helped to diversify the decision trees and prevent overfitting.

Load identification for future unknown data may be predicted using the trained random forest model. The trained model was then fed the testing set, thereby forming predictions regarding the load labels using the input characteristics. The accuracy and usefulness of the load recognition method can, therefore, be assessed by examining the difference between the projected load labels and the actual load labels in the testing set. The random forest technique was helpful for load detection as it processed several input variables and dealt with complicated correlations and interactions among characteristics. This is ideal for actual smart meter data since it can deal with categorical features and missing values. Homeowners may learn further regarding their energy consumption habits and pinpoint individual loads, adding to their total electrical consumption with the help of the random forest technique-based load classification method built on data from smart meters. This data can assist with load scheduling, response to demand, and energy conservation plans, as well as general energy management and efficiency optimisation. Figure 1 depicts the proposed smart way to find out a household's energy consumption by using a multilevel random forest on smart meters. The visualisation tool of random forest for intelligent household load identification is illustrated in Figure 2.

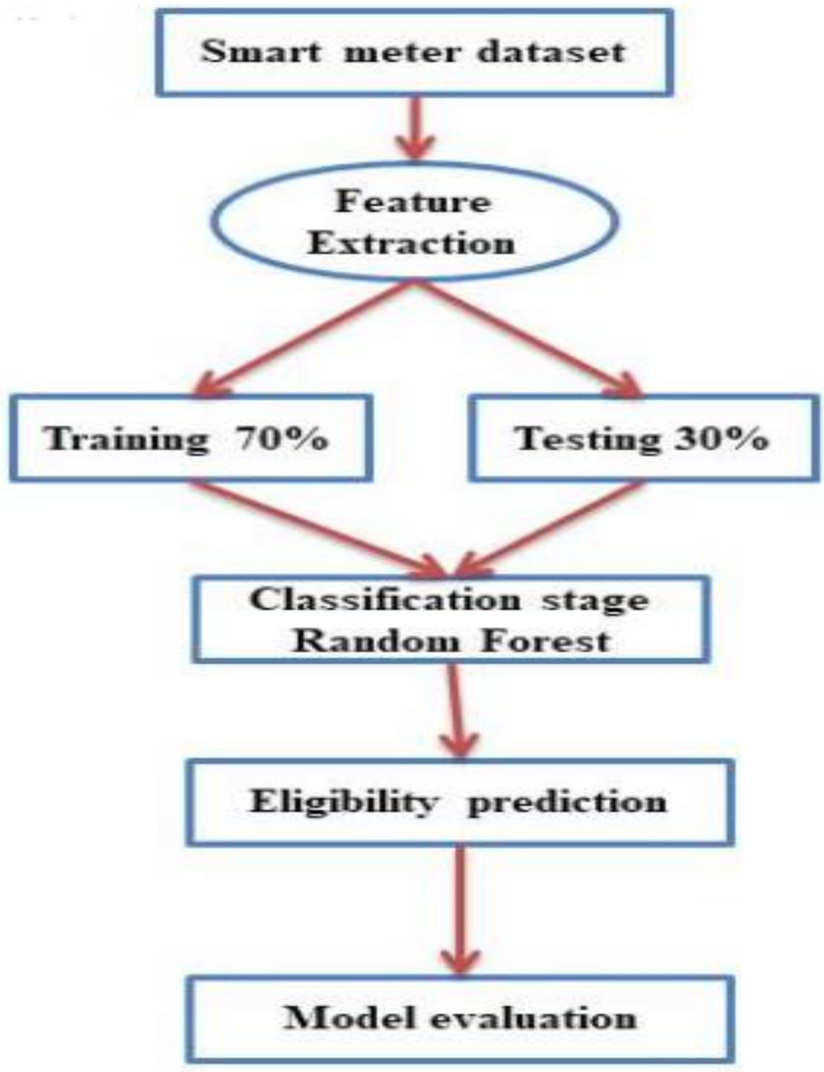

Figure 1. The proposed intelligent household load identification using multilevel random forest on smart meters

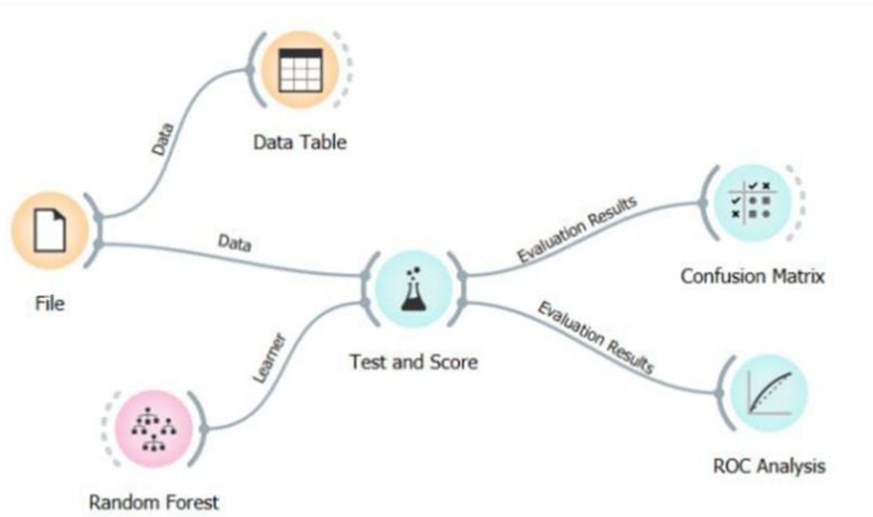

Figure 2. The visualisation tool of random forest for intelligent household load identification

The ACS-F2 database considers 15 different types of key household appliances. Two one-hour tracking sessions were performed on each of the 225 tested equipment [13–17]. Actual and reactive electrical power flows, root-mean-square (RMS) current and voltage, frequency, and power factor were only a few of the electric consumption characteristics that were tracked in this study. The sample rate of obtainment was found to be 0.1Hz.

Figure 1 depicts the manner in which a smart home centralises its data. The electric grid encompasses more than just a series of wires connecting power plants to homes. It also includes transformers, substations, and other components. High-voltage power is transmitted to neighbouring residences from local substations at a lower voltage through high-voltage transmission lines. The digital smart meter, which can monitor power use, is designed to replace traditional household meters. Additionally, smart meters may present usage statistics in near real-time on in-home monitors. The random forest is a classification algorithm or a classification method in a particular implementation. Appliances' load consumption features can be employed for classification if similar V-I trajectories are detected and recognised.

However, this does not correspond to the current study, given the type of equipment status and signature described in the section on appliance signature and features. Appliance features are categorised based on their stable and transitional state characteristics, as well as non-traditional signatures. The steady-state deviation may be influenced by the power differential between the active and passive components. Overall electrical usage measurements are usual, and in that context, it is not uncommon for standard appliance features to be mixed to produce signatures that deviate from the norm. The on/off changes of the devices are detected by the identification module, and the user is notified of the aforementioned load fluctuations. In addition, it details the steps used to achieve the new status, as described above.

In Figure 3, the live data in action can be observed. All of the gear that was used in the REFIT study was readily available for purchase and met the project's initial requirements for reliability, scalability, and performance. The energy sensors transmitted their data wirelessly to an energy aggregator that was connected to a communications gateway. Readings were also sent from the gateway connected to the broadband router to the cloud-based website. The server pulled the information from the website and stored it in a MySQL database. In terms of data gathering and in-house presence, the platform was meant to be as similar to a standard smart meter as feasible. The deployed aggregator emerged with an IHD that functioned similarly to that of a smart meter's in-home display. Smart meters, on the other hand, do not involve IAMs, which develop, test, and validate analytical approaches. Smart meters' primary benefit is their potential to provide information about a household's collective energy consumption. The energy aggregator's readings were transmitted via radio frequency (RF) to a one-phase present meter and a transmission module. In an IHD, the present price setting is used as a summarising factor. This method of expense tracking has proven useful in multiple previous research projects. It should be noted that the sensor itself does not check the voltage coming from the wall, thereby causing the generated watts number to become skewed.

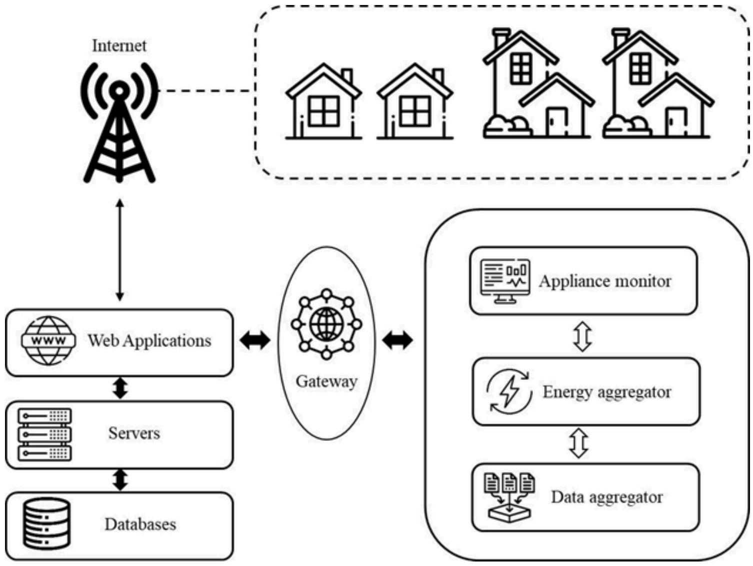

Figure 3. Real-time data collection and processing

Testing indicates that the company's sensors have an approximate error rate, despite the fact the sensor's basic functions are unknown. In these three examples, the effects of solar panel manufacture are mitigated through rewiring. The audio from the other three homes in the state was recorded despite sun interference since they could not be moved. As the sensor couldn't detect the path of the electricity in solar panels, power consumption increased in a bell-shaped form during the day, owing to weather variations, such as cloud cover. There were no data transmission collision losses as every house acquired the maximum number of I AMs that their module could manage. At regular intervals, the electrical usage of all connected appliances was sampled by each IAM. Following the compilation of all IAM data, the aggregator sent it to the gateway of the communications network. IAMs only measure current rather than voltage; therefore, they provide erroneous results when the voltage of the power source fluctuates.

A schematic of an electrical control system is depicted in Figure 4. A power control and administration system includes devices with controllers that can communicate with one another using standard protocols. Additionally, there have been multiple inquiries regarding personal tracking systems. The optimal management approaches for HVACS, such as moving consumption from peak to off-peak times, can also consider the natural thermal storage capacity of houses. A 10% decrease in a building's electricity bill is possible with this type of management. Energy resource constraints, such as those imposed by the need for independence in off-grid systems or by the overall generation limitations of the suppliers in grid-connected systems, are not taken into account by this method. Even with perfect monitoring, energy use cannot be maximised. Numerous attempts have been made to optimise energy management, including methods such as dynamic software development, real-time modelling, and multi-agent systems.

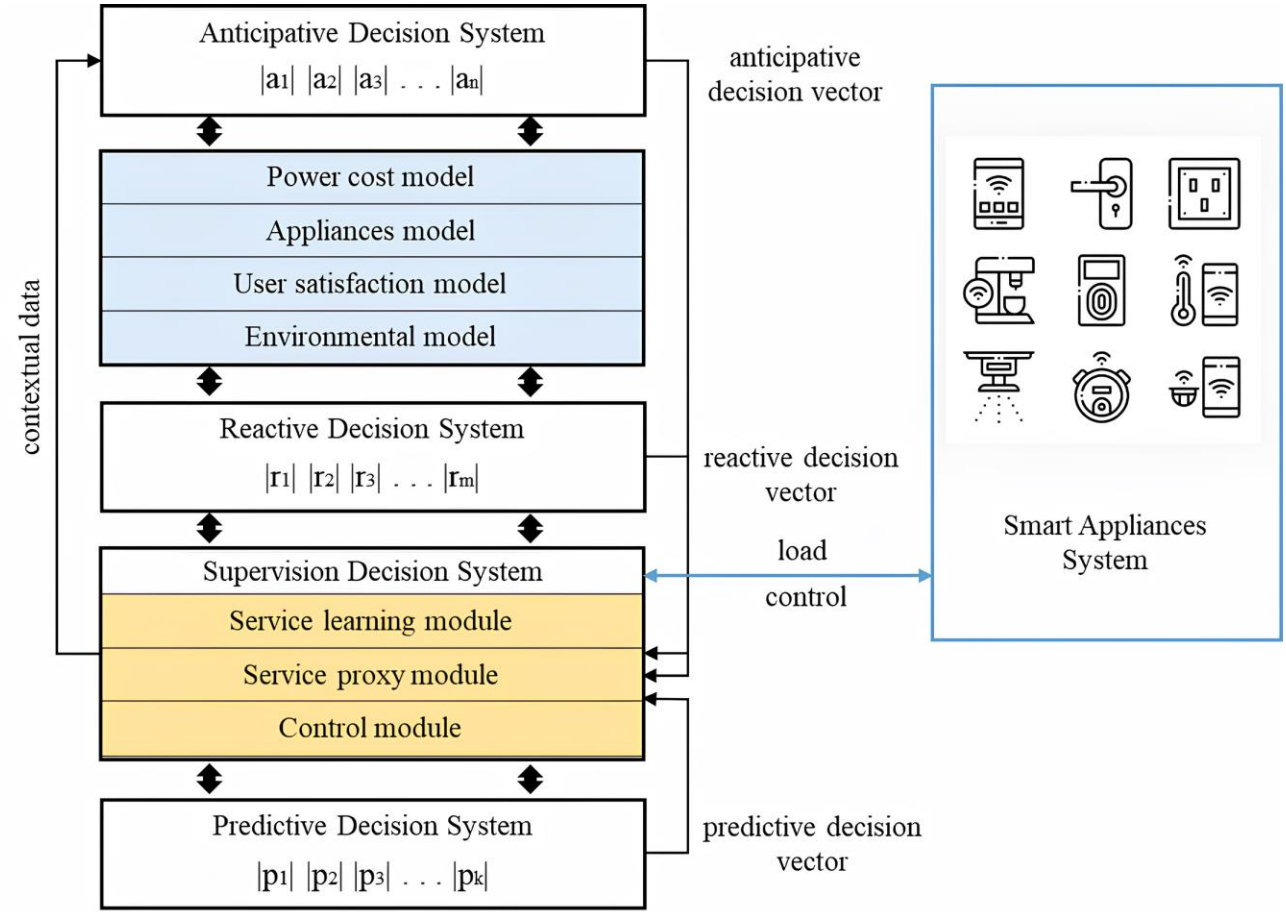

Figure 4. The creation of a system for managing power supplies

However, further concerns arise from residential energy management. Regarding systems for energy management where uncertainty plays a significant role, a three-layer architecture might match the highest possible power limitation and customer comfort criteria through a reactive layer. Large-dimensional optimisation issues can be resolved by employing a mixed linear algebra approach, which can manage millions of linear and constant variables. Services that can only be described by non-linear equations have been managed using a multi-agent approach. Each home varies and has its own set of challenges with respect to dynamic energy management. Hence, there is still a need for standards in the technological aspects of the smart home, especially in terms of the means of communication. In the Ems' houses, real-life experiments are being conducted. To verify the accuracy of the proposed algorithm and method, it is essential to perform such experiments. The pseudocode for intelligent household load identification using multilevel random forest on smart meters is presented in Algorithm1.

Algorithm1: The intelligent household load identification using random forest steps

1. Import necessary libraries and packages
2. Preprocessing:
2.1. Load the dataset from smart meters
2.2. Extract the relevant features and labels
2.3. Split the dataset into training and testing sets
3. Initialize the multilevel random forest model:
3.1. Set the number of levels and trees at each level
3.2. Set the maximum depth of each tree
3.3. Set other hyper parameters as needed
4. Training:
4.1. For each level:
4.1.1. Split the dataset into subsets based on household or appliance
4.1.2. For each subset:
4.1.2.1. Train a random forest model on the subset
4.1.2.2. Store the trained model at the corresponding level
5. Prediction:
5.1. For each level:
5.1.1. Split the dataset into subsets based on household or appliance
5.1.2. For each subset:
5.1.2.1. Retrieve the trained model at the corresponding level
5.1.2.2. Predict the load using the trained model
5.1.2.3. Store the predicted load for each subset
6. Evaluation:
6.1. Compare the predicted loads with the ground truth labels
6.2. Calculate evaluation metrics such as accuracy, precision, recall, and F1 score
6.3. Print or display the evaluation results
7. End

3. RESULTS AND DISCUSSION

The aggregate energy use of a home provided by intelligent meters is a key metric to track. To ensure the success of the research, the present cost monitoring system was chosen above alternative options available at the outset. It must be remembered that the sensor fails to keep tabs on the voltage from the wall, thereby impacting the Watts figure. A smart meter tracks how much work an appliance puts out of the house.

Saving energy and reducing power waste in buildings is the ultimate objective of a micro-moment-based anomaly detection system. Due to the intelligent household load identification using random forest on end-users flawed actions, it is in the best interest to detect as many anomalies as possible. However, this varies for people who engage in wasteful electrical practices. Indirect feedback on energy use from utilities to consumers has been shown to boost power savings by 15%. Furthermore, direct appliance usage data provided to end users has the potential to reduce energy use by 25%. Accessibility to detecting anomalies reported by end users increases to 97.4% for intelligent household load identification using random forest savings rate.

The domestic energy consumption management is displayed in Table 1. Depending on their comfort level, the state of the economy, and the state of the energy market, residents can adjust their electricity use. A healthy equilibrium between energy production and consumption may be found with the help of an EMS installed in the home. Energy can be conserved by turning off all electronics and only leave on the lights if required while the room is not in use. Since electricity is used even when appliances are turned off, it is vital only to plug them in when they are being used. The proposed solution reduces energy use by 99.2 percent compared to standard practices.

Table 1 provides statistics relating to the decrease of residential energy usage utilising multiple approaches, such as IoT and the Non-Intrusive Load Monitoring (NILM). The table depicts the percentage of energy savings realised by various strategies for reducing energy usage over a range of appliance counts. In this column, we display the various possibilities based on the number of appliances in use. The rows represent several possible configurations, with anything from 10 to 100 appliances per row. Percentages in the IoT column indicate the level of energy conservation with the help of IoT technology. In a smart home, the electrical power use of devices and systems may be minimised and managed with the help of IoT devices. The values in this column depict how well IoT works to cut energy consumption across a range of appliance densities.

However, the numbers in the column for Non-Intrusive Load Monitoring, or NILM, represent the amount of energy saved due to this type of monitoring. With NILM, there is no need to install sensors on every device, as NILM effectively monitors and identifies energy usage trends remotely. It is useful to learn about home energy use patterns. The figures in this column demonstrate the level of energy conservation by using NILM with various appliance counts.

The last column depicts energy savings from employing the Random Forest method. This method is highlighted with respect to machine learning, prediction modelling and classification tasks, and is used as a means of cutting back on power usage. The number of devices in a home has a significant impact on the percentage of energy savings achieved by using IoT, NILM, or Random Forest. It appears that the higher the number of appliances, the more difficult it is to achieve substantial energy savings.

Nonetheless, for most circumstances, the Random Forest approach looks to surpass both IoT and NILM in terms of energy savings. This suggests that Random Forest and other machine learning techniques may be used to efficiently optimise energy usage in a home with several appliances. It was observed that the outcomes were not uniformly consistent. As seen in Table 1, when the number of appliances was 60, the IoT approach outperformed NILM, although in most other circumstances, NILM was preferable. This demonstrates the manner in which the efficiency of these techniques may vary amongst households and appliances. The percentages in the table depict the reductions in energy use. These findings may be interpreted in terms of the viability of energy saving initiatives. For instance, the table may be used to calculate an approximate number of appliances and approach required to accomplish a desired percentage reduction in a household's energy use. In conclusion, the following table illustrates the manner in which the possible energy savings achieved by various approaches differ with the number of devices in a home. It also stresses the significance of tailoring energy-saving strategies to individual households' features and objectives.

Table 1. Reducing Domestic Energy Use

Number of Appliances	IoT	NILM	Random Forest
10	59.3	66	86
20	55	67	82
30	50	64	90
40	52	78	94.7
50	55	67	92.5
60	58	70	95
70	44	68	96
80	49	77	94.3
90	57	74	87
100	42	79	99.2

In addition, power outages can be caused by several different reasons, including shorts in circuits, substation failing, and distribution line damage. Intelligent meter analysis of data focuses on both billing and preventing power outages. These include alerts in the event of an outage, pinpointing its location, and documenting its repair. Data requirements, system integration issues, and the operation of outage management software were examined with the help of a two-step process to identify and map the affected region during an outage. Topology analysis was used first to streamline the physical distribution network before a smart meter data was used to specify the outage's origin and determine the extent of its impact through communication. The proposed method improved load-shedding control by 96.7% over the status quo. In the event of an electrical outage, an intelligent meter-based failure region predicting tool was provided.

The extremely effective computation is displayed in Table 2. Large smart meter datasets require high-performance computing solutions; however, the majority of existing approaches are only suitable for handling small datasets. Platform as a service, software as a service, infrastructure as a service, and economical computation architecture for distributed computing resources on the internet are all examples of storage for data systems that may be used to deliver designed to adapt (DTA) services. Maximising the use of grid computing is a key challenge in data from smart meters processing. In addition, processing on a graphics card is one of the methods of fast computing. The efficiency of parallel processing is often seen to be remarkable. Various activities requiring GPU processing should have access to a variety of approaches. The proposed strategy improves efficiency by 98.6% percentage points over current practices.

Table 2. Extremely effective computation

Number of Appliances	IoT	NILM	Random Forest
10	51	67.9	79
20	57.3	74	88
30	58	78	82
40	59	64.8	87
50	55.3	75	93
60	54	79	89.3
70	63.6	66.5	98.3
80	55.4	79.7	90
90	58	83.4	94
100	55.2	79.1	98.6

The development of smart metering and the proliferation of distributed renewable energy go hand in hand. A typical smart home makes use of electric, gas, and solar power for cooling and heating, respectively. New technologies, such as rooftop photovoltaic solar panels, storage of energy, and electric vehicles, will lead to a reorganisation of distribution networks in the future. Energy consumption patterns and netload profiles will also undergo significant changes as a result of the extensive use of renewable energy generated behind the meter. Due to renewable energy's rising market share, conventional load profiling techniques must be updated. Moreover, combining weather information with electricity pricing data and netload statistics can yield further insights, thereby helping to recover the pre-change load profile. It is standard practice to employ energy storage to smooth out fluctuations in renewable power production. The efficiency, effectiveness, and smoothness of energy system transitions, as well as the load-shedding management and residential energy consumption control, were all assessed using the suggested technique.

The simplest type, i.e., the binary results, arise from a screening test indicating whether the classifier is uninfected (Dx = 0) or correct (Dx = 1). A screening test indicates whether or not a classifier is likely to be correct. The results of the Roc curve are presented in Figures 5 and 6.

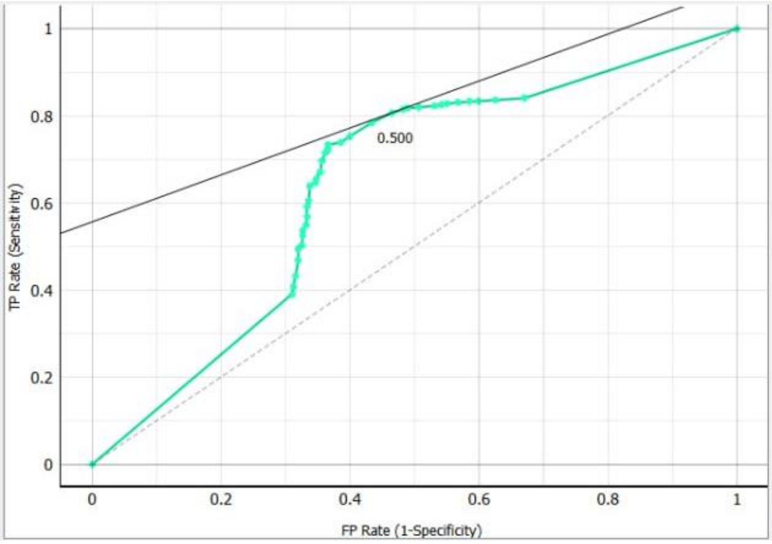

Figure 5. The test indicates an uninfected random forest DX = 0

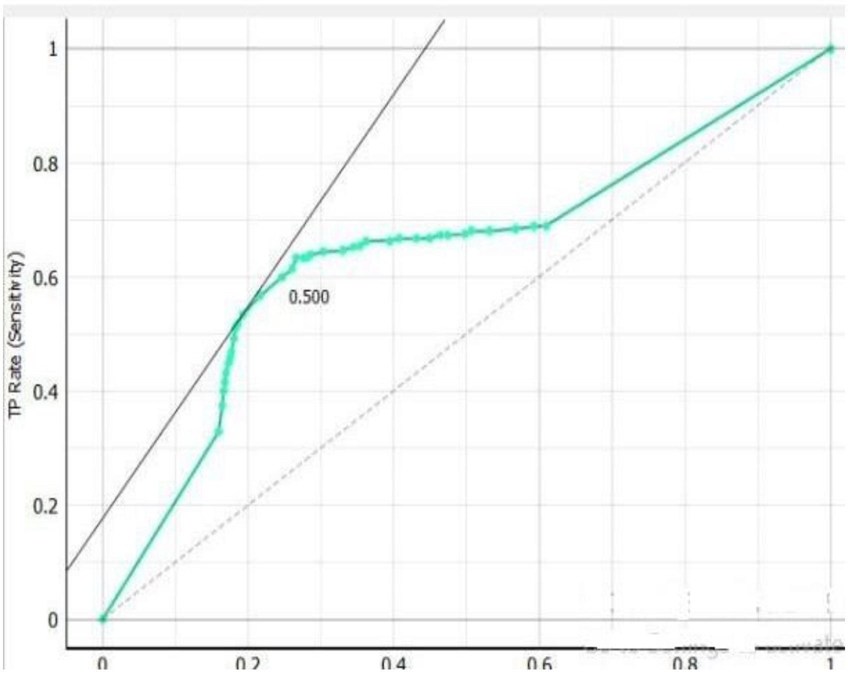

Figure 6. The test indicates the random forest has DX=1

4. CONCLUSION

Home energy consumption varies from person to person. The suggested framework allows for the estimation of house characteristics by employing energy usage data. Smart meters analyse univariate time series data to predict a building's population, occupants' activity levels, energy consumption, as well as the number of bedrooms. This allows the method to become more dependent on the circumstances and duration of the device being used to conduct all the calculations. The researchers discovered this finding via a random forest technique on energy consumption data from home appliances. DTA-LI can monitor appliance power consumption with the help of a cheap power meter connection coupled to the control hub. In order to adopt energy-efficient technologies in housing projects, it is crucial to understand the features of each property. By analysing the data in these groups, it is possible to discover how various model characteristics impact energy use. Furthermore, the researchers have also shown that the proposed method, by analysing the temporal correlations between variables, may provide useful insights regarding a home's geo-demographic level. The proposed approach, which is based on a random forest technique, improves the home power savings rate by 99.2% and the load management efficiency by 98.6%. Future studies might investigate the viability of using these techniques in the design of forecasting systems for aggregate and divided intelligent meter time series, along with using techniques such as fuzzy logic and federated learning.

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CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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