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Intelligent Load Identification of Household Smart Meters Using Multilevel Decision Tree and Data Fusion Techniques

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Abstract

The decision tree algorithm-based load identification (DTA-LI) system's fusion data method is crucial in the monitoring of appliance loads for the purposes of improving energy efficiency and management. Common home electrical devices are identified and classified from smart meter data through the analysis of voltage and current variations, allowing for the measurement of energy usage in residential buildings. A load identification system based on a decision tree algorithm may infer information about the residents of a building based on their energy usage habits. Better power savings rates, load shedding management, and overall electrical system performance are the results of the clusters' ability to capture families' purchasing patterns and geodemographic segmentation. The DTA-LI system's fusion data method presents a promising avenue for improving residential buildings' energy performance and lowering their carbon footprint, especially in light of the widespread use of smart meters in recent years.

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1. Introduction

Smart home meters with intelligent load identification to detect and categorize typical home activities using smart meter data, a technique called "Using Multilevel Decision Tree and Data Fusion Techniques" has been developed. The method takes a typical reading from a home's smart meter and utilizes multilayer decision tree algorithms and data fusion methods to separate the primary power measurement into its components and identify common household electrical goods. The purpose of this framework is to improve the electricity-saving rate, control household energy consumption, manage load shedding, increase energy efficiency, and facilitate the transition of energy systems by inferring the features of households in residential buildings [1]. Electrical energy is the most essential and handy energy source for businesses and people [1]. Electrical energy consumption has continued to rise at an alarming pace over many decades [2]. It is becoming more difficult to keep up with the ever-increasing demand for power as the world's population grows and new technologies are developed [3]. Households utilize a substantial amount of energy for many reasons, including heating and cooling, lighting, and other electrical equipment [4]. Energy conservation has gone from a choice to a requirement due to the limited resources available to fulfill the population's present and future energy consumption demands [5]. Energy conservation can be done using energy more effectively. Reducing energy consumption would improve environmental protection, as a fall in demand necessitates less energy generation from non-renewable sources [6]. Due to this, it will have less influence on climate change and the greenhouse effect on the environment [7]. Due to the ever-increasing variety of home electrical appliances, it's tough to determine, in which ones contribute significantly to the overall power cost [8]. Consumers must be educated about the elements that affect their overall power use to avoid overconsumption [9]. Supplying customers with real-time power usage data at the aggregate level helps them adjust their behavior and save 10–15% in power expenses [10].

An electrical load identification method breaks down the overall amount of energy utilized in a given period into more specific numbers [11]. Due to this tool, customers will identify electrical gadgets' appliances, operating modes, and consumption information [12]. As a general rule, sensors collect information about appliance use, such as the amount of electricity used and the time and frequency of use, for a limited duration [13]. Afterward, the data are passed to a processing system for processing and storage, from whence it can be retrieved and shown at any given moment [14]. Using a single sensor at the meter instead of sensors for each appliance is more practical and less expensive. Thus, a more efficient system is achieved, requiring more complicated algorithms to identify the loads [15]. Identifying household loads are used to assist consumers in arranging their energy usage more efficiently [16]. It is a foundation for developing a demand-side management strategy [17]. A household's complete power usage profile is broken down into individual load signals in load monitoring [18]. No physical power meters are required for each load to perform the disaggregation process [19]. The signatures of electrical loads are utilized to determine at a certain point in time or over a given period [20].

In this paper, electric utility companies and their customers benefit greatly from using load monitors. It helps them better understand how much electricity is being used and does so at a reasonable price. Energy reduction can be achieved through the use of load-specific feedback. With the extensive deployment of smart meters, load monitoring has grown in popularity, allowing for a better knowledge of customer behavior and improved demand-side management. A smart meter can determine the signature of electrical loads in real time and transmit this information to the utility. Load signatures might be utilized for monitoring, diagnostics, and power quality management on the low-voltage substation. Each customer's energy use is normally recorded at the building level through a smart meter. This data has several possibilities if it can reliably identify appliance consumption from smart meter data. The main contribution of this paper is,

- Customers will receive improved short- and long-term demand profiles, geographic load forecasts, and information on their energy use and the factors contributing to it
- Consumer profiling, categorization, and transactive energy are all components of measuring and validating energy efficiency
- It is feasible to infer behavioral patterns of the home's residents, such as occupancy, sleeping patterns, and other everyday activities, from statistics on appliance consumption.

Modern industrial environments saw a significant rise in the development of smart meter technologies in the context of a smart grid-linked home load system. The smart meter's application requires an understanding of the current load pattern. Individual load power consumption and operational behavior could be assessed using the well-known non-intrusive load monitoring (NILM) technique [21]. It was tested using PLAID databases and compared to some of the most current methods. The ability of the suggested technique was shown by appropriate simulations and experimentally generated dataset analysis on a residential system.

The relevance of electricity load forecasting for energy management, infrastructure planning, and budgeting has drawn academic and industrial interest. In recent years, the spread of smart meters and other sensors has opened up new possibilities for sensor-based load forecasting at the building and home levels. Machine learning algorithms like recurrent neural networks demonstrated significant effectiveness [22]. However, these approaches use offline learning: They were trained only once and cannot learn from freshly incoming data. Compared to existing online and offline algorithms, the suggested method outperforms the stand-alone offline long short-term memory network.

Smart meters were increasingly being replaced by traditional electromechanical meters due to their major advantages, such as direct load management for demand response and energy conservation. The privacy of smart meter users was compromised in some ways, one of which being occupancy detection. The first investigates the viability of an occupancy detection attack and yield superior results using the long short-term memory method. A counterattack to control energy utilization was Adversarial Machine Learning-Based Occupancy Detection Avoidance (AMLODA) [23].

The proposed AMLODA method, which safeguards client privacy, could reduce occupancy detection assaults by modifying the attack models' MCC values. The type of energy that was most commonly used was electricity. The use of an Internet of Things (IoT) service-oriented electrical energy management system (EMS) to intrusively monitor and regulate electrical loads in response to demand-response schemes for demand-side management allowed smart grids to meet the steadily rising electrical energy demands of their customers [24]. [25] Recent smart grid research has focused on NILM, a realistic and affordable replacement for EMS. A multi-objective evolutionary computing-based NILM without training was used to test the smart IoT-focused home EMS in a real-world setting. Prognostication of load activities in home automation systems was already required to achieve the lowest possible power consumption. Smart houses were equipped with a variety of electrical appliances. For the disaggregation of electrical devices, a viable mixed technique was proposed in the present research using the factorial hidden markov model (FHMM), and electrical device locations could be accurately simulated [26]. The suggested technique recorded every electrical device's current location in the dataset. Due to the FHMM, the examined databanks and calculation time had been significantly reduced for the constraint. Six smart homes were tested to see whether the suggested method was as fast and accurate as others in answering questions about important data [25,27].

There are numerous methods to organize the remaining decision tree algorithm-based load identification (DTA-LI) system components. Section 2 briefly summarizes the creative concepts discussed and applied in this work. The results and analyses of the investigation are summarized in section 3 of the report. Section 4 of the DTA-LI system includes an in-depth analysis of conclusions.

2. Proposed Method: DTA-LI System of Households Using Smart Meter

A smart meter's data can reveal a wide range of information, depending on the temporal resolution of the information. Specifics are provided on the sample frequencies and the appliances detected at each sampling frequency. When inferring home occupancy, hourly or half-hourly data from smart meters can be utilized. At the same time, higher-resolution data can be used to obtain more specific information on the use of each appliance. Higher-order harmonics can be used to identify a variety of appliances, including consumer electronics and lighting loads, when combined with exceptionally high-resolution data.

The information centralization of a smart house is depicted in Figure 1. The electric grid is a system of transformers, substations, and transmission lines that do more than move energy from a power plant to a dwelling. Local substations reduce high-voltage electricity to a lower voltage and transmit it over high-voltage transmission lines to nearby

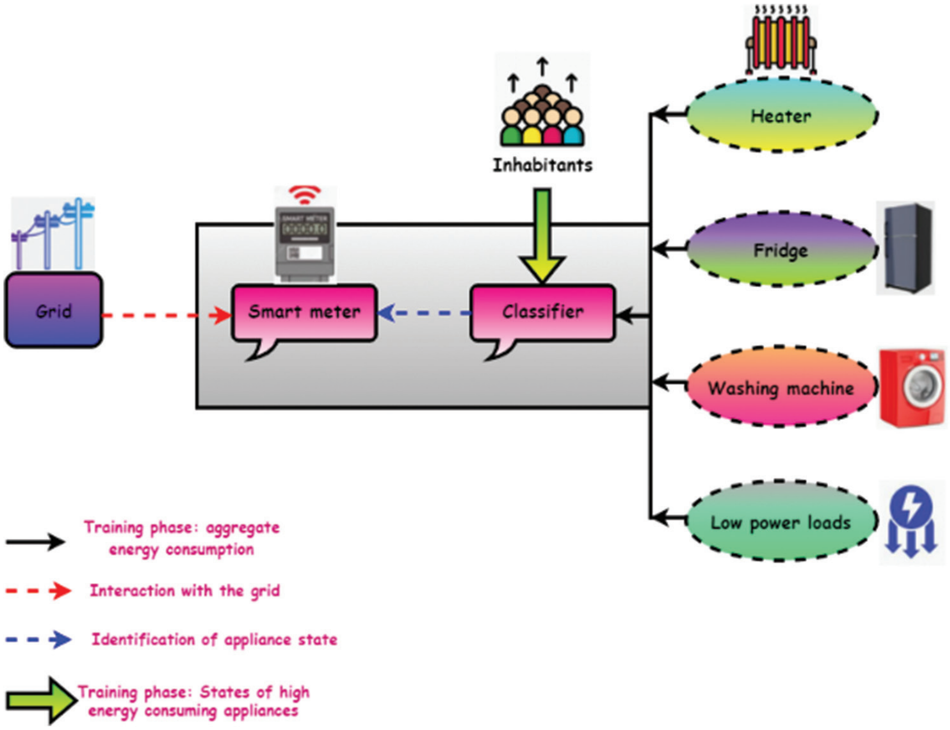

Figure 1: Centralization of the information of a smart home based on data fusion techniques.

homes. Replacement for conventional meters in the house, the smart meter is a digital meter that can track electricity consumption. In addition, smart meters have in-home displays, and consumption data have been shown in near real-time. A classifier is an algorithm that performs classification, particularly in a specific implementation. Using detection and recognition to identify comparable V-I trajectories in the load consumption signatures of appliances can assist in classifying loads.

According to the sort of appliance state and signature indicated above in the appliance signature and features section, this cannot be the case. Stable and transient state characteristics, including non-traditional signatures, are used to classify appliance attributes. The power difference between actual and reactive power can affect the steady-state variation. According to the routine of total power consumption measurements, non-traditional signatures are commonly created by mixing conventional appliance characteristics. The recognition module detects changes in the devices' on/off states and alerts the user using the previously mentioned load fluctuations. In addition, it indicates the actions detailed in the subsections above on the change of status.

On the side of the hyperplane, the measured values fall. They are expected to belong to a certain category in that space. A hyperplane $g(y)$ is specified as

$$g(y) = \gamma_0 - \gamma^S y \tag{1}$$

As shown in equation (1), γ_0 is denoted as the input vector, while γ^S indicates the bias, and y represents a certain set of characteristics.

Scaling up and down gives endless possibilities for representing the ideal hyperplane. The depiction selected is given as,

$$\left\|\gamma_0 - \gamma^S y\right\| = 1$$

$$distance = \frac{\left\|\gamma_0 - \gamma^S y\right\|}{|\gamma|} \tag{2}$$

As shown in equation (2), where y is the distance between the points, and γ denotes the support vectors.

Figure 2 shows the DTA-LI system. The raw smart meter data are first processed, and all data points should be modified similarly to make data analysis easier. The categorization technique of load monitoring can be used to monitor the power consumption of home appliances. Data collection and processing starting with current, voltage, and power usage data and denoising those readings, goes from there. These measurements are used in the process of feature extraction for the detection of appliances. It is performed at a certain frequency to get the best results from the electrical load measurement. Smart meters are now the most prevalent method for determining how much electricity is used. Starting with the data acquisition phase of data collecting, one can identify patterns and even discriminate characteristics using a smart meter-feature extraction for appliances.

Appliance voltage and current readings and their waveforms are used to predict a feature that can be used to calculate reactive and active power states. In addition, the on/off state change of appliances on power consumption data can be retrieved for appliance signature for event detection. The power level analysis measures the change in the device's

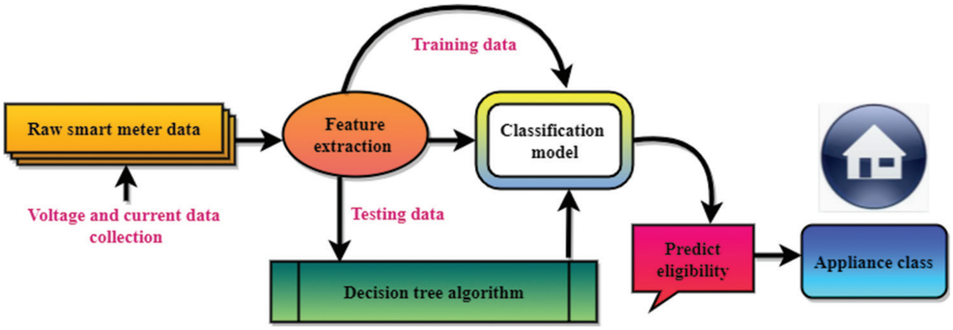

Figure 2: Decision tree algorithm-based load identification system.

status to determine whether an appliance is on or off. The load characteristics can be derived based on load signatures utilizing various approaches to give appliance signature information. When distinguishing between various appliances often represented in vectors and dimensions, statistical analysis techniques calculate the number of features. Then, the attributes picked can enhance the categorization capacity of the load monitoring system. The physical load characteristics of the transient energy and the typical steady-state power features are used to generate the appliance's actual and reactive power. It is possible to process feature extraction in various ways to provide an accurate appliance dataset that can be utilized next.

A regular hyperplane's numerator is one, and the range to the training set M is described as,

$$min_{\gamma,\gamma_0} M(\gamma)=\frac{1}{2}\|\gamma\|^2, z_k(\gamma_0-\gamma^S y_k)\leq 1 \tag{3}$$

As shown in equation (3), each of the training examples' labels is represented by z_k in this diagram. An optimization issue can be addressed by y_k employing multipliers to determine an optimum hyperplane's weight vector and bias.

An observation's output classification is determined by averaging the $h(y)$ closest observers' responses are stated as follows,

$$G=\{(y_1,z_1),\ldots.(y_k,z_k)\}$$

$$h(y)=z_m \text{ where } m=g(y,y_n) \tag{4}$$

As shown in equation (4), the training process G consists of z_m objects and their associated classes (y_k, z_k).

During the load recognition phase, the appliance's load consumption features are compared to the database's characteristics gathered during the appliance's operational event. The starting condition of the appliance is critical to understanding the appliance's current-voltage pattern to choose an appropriate classification approach from either supervised or unsupervised algorithms. The identification process uses the classification of electrical appliances based on a current pattern or V-I trajectory attributes. After evaluating several supervised classifier approaches, we employed a training data model for classification in this study. The decision tree algorithm is used to identify and classify the appliances.

Figure 3 shows the data collected in real-time. All the equipment utilized in the REFIT research is commercial off-the-shelf gear that could be purchased at the beginning of the study for dependability, scalability, and performance. An energy aggregator linked to a communications gateway received wireless readings from energy sensors. The online portal in the cloud received readings from the gateway, which has been linked to the broadband router. The data are obtained from the online site and saved in a MySQL database by the server. The Platform is designed to be as close to a regular smart meter as possible in data collection and in home presence. A comparable in-home display IHD to that found on a smart meter is included with the utilized aggregator.

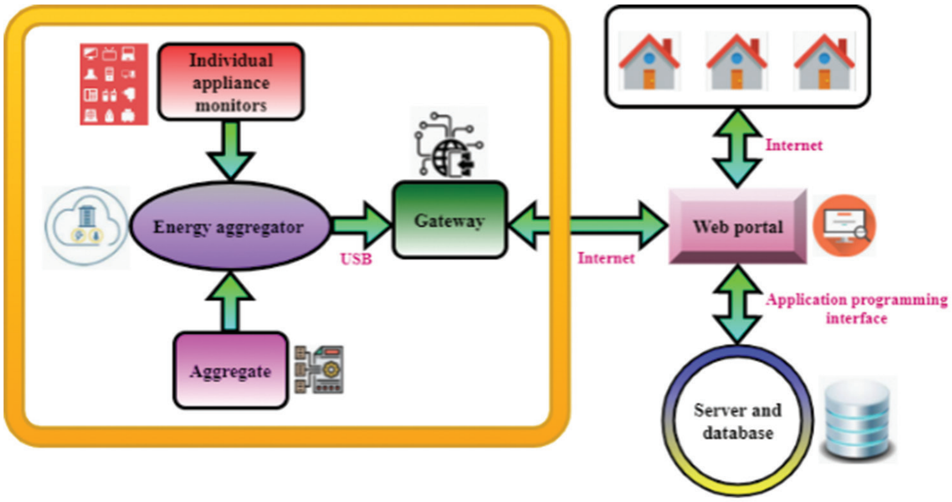

Figure 3: Data collecting in real-time.

On the other hand, the smart meter will not have individual appliance monitors (IAMs), and they can be used to create, model, test, and verify analytical methodologies. As smart meters would be able to offer, the essential measurement in each home is the total energy usage of the whole family. Measurements from the energy aggregator were sent wirelessly to the single-phase current clamp and a transmission module using radio frequency (RF). With an IHD, the current cost environment is employed as the aggregator. The current cost-monitoring device has been utilized effectively in numerous earlier studies. It is important to remember that the sensor does not monitor the voltage from the mains. Therefore, the watts figure produced can become inaccurate.

Although the sensor's fundamental workings remain a mystery, testing shows that the manufacturer's sensors have a relative error rate. Rewiring is performed to eliminate the impact of solar panel production in three instances. The remaining three houses could not be rearranged; thus, their audio has been captured with solar interference in the state. Power usage rose in a bell-curve-shaped pattern throughout the day due to weather changes, such as cloud cover, because a sensor could not tell the direction of power flow in solar panels. All homes received the maximum amount of I AMs that the corresponding module could handle without losing any data transmission collisions. Each IAM sampled the power consumption of each associated appliance at a predetermined interval. The aggregator collected all IAM readings, then forwarded them to the communications gateway through the communications network's gateway. In a power supply voltage fluctuation, the IAMs only measure current and not voltage, leading to inaccurate readings.

Figure 4 shows the design of a power management system. An energy management and control system comprises appliances with controllers capable of communicating using established protocols. There have been several studies on home-based tracking systems by different individuals. Houses' inherent thermal storage capacity can be considered in designing optimum management techniques for HVACS, such as shifting demand from peak to off-peak periods. With this kind of management, a building's power costs can be reduced by 10%. This technique does not account for the energy resource restrictions, which often depend on the autonomy requirements of off-grid systems or the overall power output limits of the providers in grid-connected systems. Energy efficiency cannot be maximized even if perfect tracking is used. Optimization strategies for energy management have been tried, including dynamic programming, real-time simulations, and multi-agent approaches.

Energy management in living spaces raises additional issues: A three-layer design could meet the maximum available electrical power restriction and the user satisfaction requirements, through a reactive layer, in EMS where uncertainty is a major factor. A mixed-integer linear programming methodology to handle thousands of binary and continuous variables solves large-dimensional optimization problems. A multi-agent technique has been used to manage services that non-linear equations can only describe. Predicted future usage of an appliance dynamic energy management issues to tackle – every living environment is unique and constantly growing. Standards are still needed in the smart home's technical components, particularly when it comes to communication methods. There are real-life experiments in the Ems homes. Performing these experiments is critical to validating the algorithm and technique presented.

Researchers can monitor, record, and modify daily activities and interactions in a real-world setting at the Place Lab to learn more about how people interact at home. For many days or weeks at a time, Place Lab volunteers see it as a home away from home. Meanwhile, sensors built into the building's structure record a full account of their operations. From

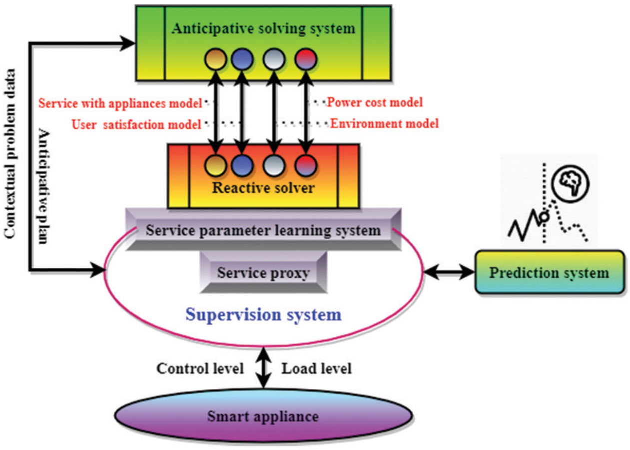

Figure 4: The design of a power management system.

the interior of the house, energy management: While employing smart control to automate some decision-making, there are benefits in technological design and user interface for systems that seek to provide people with information at teachable times. Tools and algorithms for power management of home appliances must be developed to predict certain circumstances and consider the current status of the housing system and tenant expectations.

House automation is a more modest goal than energy-smart homes, achieved through a more comprehensive global control system. Energy production and consumption can be balanced at all sizes, from individual homes to whole communities. Energy pricing and unbalancing orders should be taken into consideration by smart houses, which should be able to adjust their appliance behavior to meet the needs of the residents and those of external actors. Small and inexpensive state-change sensors have previously been used to construct a system for detecting activities in the house. It is possible to install the sensors in any household setting fast and easily. It offers an alternative to sensors such as cameras and microphones, which might be seen as intrusive. Appliances' energy usage is the only home sensor for this study's prediction system.

Predictive talents are necessary for anticipating adverse scenarios. Detailed weather predictions for real-world residential areas must consider architectural features and shading masks. Residents should be foreseen to avoid grilling them about their plans. Oven-use forecasting can be a challenging challenge with no apparent pattern. They build new prediction algorithms that use historical data and occupants' wishes expressed through effective Human-Machine Interfaces. For some time now, data privacy has been a point of debate. Sensors are a source of worry due to the lack of government regulation. Efforts in this area should respect participants' privacy as much as possible and be appropriately controlled.

Figure 5 shows the detection of inappropriate energy usage. Sensors and utility sub-meters in the building are utilized to gather this data. Based on unique occupancy patterns, inappropriate usage by line service can be identified. Google, on the other hand, uses micro-moment characteristics to forecast consumer behavior for marketing purposes. It has not yet been researched how to harness micro-moments for energy applications, specifically aberrant energy use. Many sensors are employed during the fieldwork phase to collect unprocessed data. Data are cleaned and pre-processed from various energy and occupancy sensors to remove or correct any false entries.

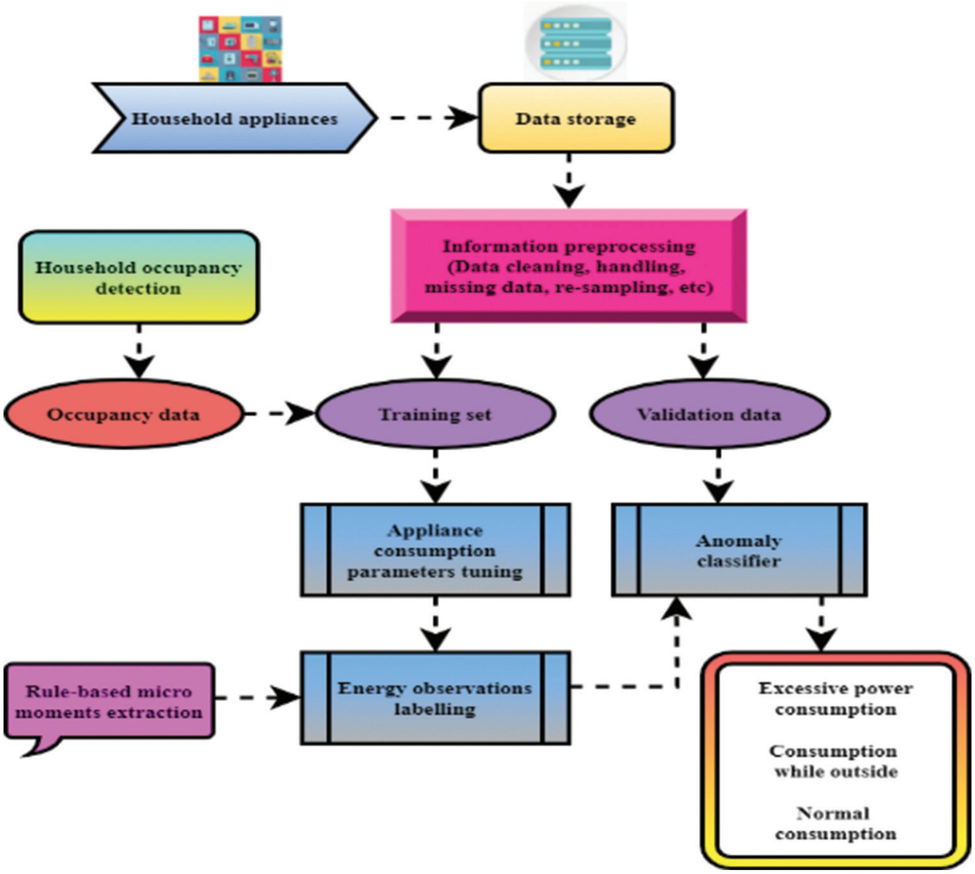

Figure 5: Detection of inappropriate energy usage.

The missing values and intriguing attributes have been lost in collecting the footprints. Device failure is the most common explanation for the lack of these data. In addition, some data are erroneous or include outliers. Using a data cleansing technique is critical in this situation.

Time series forecasting systems can be compared using a variety of measures for assessing forecasting inaccuracy which is defined as,

$$MAE(s) = \frac{1}{k}\sum_{s=1}^{k}\left|z_s - \underline{z}_s\right| \tag{5}$$

Errors in the Root Mean Square (*ERMS*) are stated as,

$$ERMS(s) = \sqrt{\frac{\sum_{s=1}^{k}(z_s - \underline{z}_s^{2})}{k}} \tag{6}$$

The connection can be inflated if two high loads are measured at a distance of times described as,

$$MASE(s) = \frac{1}{K}\sum_{S=1}^{k}\left(\frac{\left|z_s - \underline{z}_s\right|}{\frac{1}{k-1}\sum_{j=1}^{k}\left|z_j - z_{j-1}\right|}\right) \tag{7}$$

As shown in equations (5), (6), and (7), *MAE* represents a Mean Absolute Error, z_s denoted the actual value at time *s*, and that *k* is the number of measurements, $\underline{z}_s$ is the predicted value. Errors on average z_j are ignored, regardless of whether the predicted values are greater or lower than the actual values and mean average scaled error (*MASE*).

The APSR calculates the percentage difference between the daily peak consumption and the expected daily peak value is defined as,

$$APSR = \left|\frac{z_{max} + \underline{z}_{max}}{z_{max}}\right| \times 100 \tag{8}$$

As shown in equation (8), under various circumstances z_{max}, the forecasting model delivers different values for the stated metrics $\underline{z}_{max}$.

All missing variables in power datasets can be filled in using the ascribed mean value. It is difficult to determine whether an electrical item is being used excessively, particularly given the scarcity of resources for monitoring appliance power use. When it comes to excessive use, they describe it as the length of time an appliance operates and its maximum wattage. Each appliance must be defined to link recorded data to each appliance's usage outside the room micro-moment. The properties of the micro-moment are extracted from a dataset using a rule-based method. Dates, time intervals, device identifiers, power usage, and occupancy patterns are all included in each dataset.

3. Numerical Result

As smart meters would offer, household aggregate energy consumption has been the most crucial measurement in each house. The current cost monitoring technology is selected below alternative possibilities available at the study's inception to ensure the study's success. It is important to remember that the sensor does not monitor the voltage from the mains; therefore, the Watts value produced could be inaccurate. A smart meter monitors the loads in a household appliance.

Figure 6 shows the electricity-saving rate. The ultimate goal of an anomaly detection system based on micro-moments is to decrease power waste and maximize energy savings in buildings. Because the DTA-LI system is highly dependent on defective end-user behavior, detecting as many abnormalities as possible saves more energy than otherwise. The opposite is true for users with only a few bad habits regarding electricity usage. It has also been demonstrated that providing end users with indirect feedback on their energy usage resulted in an increase of 12% in electricity savings. If end consumers are given direct appliance consumption information, 20% of energy might be saved. If end users have access to anomaly detection feedback, the saving rate in the DTA-LI system can be raised to 95.1%.

Table 1 shows the control of household energy consumption. Inhabitants can alter their power use based on anticipated comfort, energy price volatility, and other factors. A home EMS can identify the optimal energy allocation plan and a good balance between the amounts of energy generated and consumed. When not in use, disconnect all electrical gadgets in the room and only leave the lights on when necessary. The use of electrical equipment, even when they are not in use, consumes energy; therefore, plugging in just when necessary can help preserve energy in the house. Compared to the existing approaches, the suggested method improves by 98.4% in energy consumption ratio.

Figure 7 shows the management of the load-shedding ratio. Short circuits, station failure, and distribution line damage are all possible causes of a power outage. Aside from payment, outage control is a top priority in smart meter

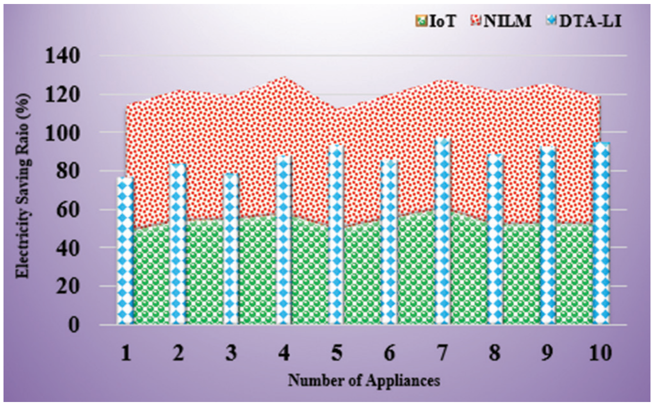

Figure 6: Electricity saving rate.

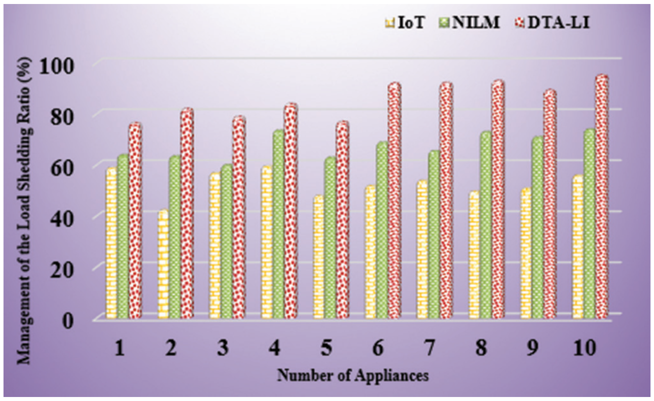

Figure 7: Management of the load shedding.

Table 1: Control of household energy consumption

Number of appliances	IoT	NILM	DTA-LI
10	56.8	64	79
20	51	63.5	84
30	45	60	88
40	48.7	73.6	83.7
50	50.4	63	90.3
60	54	68.9	91
70	48	65.5	92
80	46.9	73	93.9
90	53	71	82
100	47	74	98.4

NILM: Non-intrusive load monitoring, DTA-LI: Decision tree algorithm-based load identification data analysis. Notification of an outage, location, and proof of restoration are all included in the study. Data needs, system integration concerns, and how outage management applications function have been discussed. The outage area is discovered and mapped using a two-stage approach. First, the physical distribution network is reduced using topology analysis; in the second step, the outage region is located using smart meter information, which evaluates the effects of communication. The suggested solution increases load-shedding management by 95.3% compared to the current approach. A smart meter-based outage location prediction system is given to locate and restore power failures promptly.

Table 2 shows the computation with a high degree of efficiency. The bulk of smart meter data processing strategies relevant to small data sets can never be appropriate for huge data sets, leading to high-performance computation. A variety of data storage architectures can provide DTA services, including platform as a service, software as a service, infrastructure as a service (IaaS), and efficient computing architecture that distributes computer resources over the internet (IaaS). One of the most crucial issues in smart meter data analysis is taking maximum advantage of grid computing. A high-performance computing technique is graphics card processing. Parallel processing is capable of being very effective. There should be a wide range of methods for various GPU processing tasks. Compared to existing methods, the suggested method creates an efficiency ratio of 97.6%.

Figure 8 shows the system transition in energy. Distributed renewable energy and various energy systems are inextricably linked in the evolution of smart metering. Cooling, heating, gas, and electricity all play a role in a typical smart house. Future distribution networks will be restructured with newcomers such as rooftop photovoltaic, energy storage, and electric vehicles. The high penetration of behind-the-meter renewable energy will considerably alter energy consumption habits and net load profiles. The increased penetration of renewable energy necessitates changing traditional load profiling methodologies. Additional information can be obtained by integrating meteorological data with power prices and statistics on net load. Thus, the original load profile can be restored. Energy storage is

Table 2: Computation with a high degree of efficiency

Number of appliances	IoT	NILM	DTA-LI
10	49	65.7	77
20	54.5	71	84
30	55	75	79
40	58	62.9	88
50	50.1	72	94
60	56	78	85.7
70	60.8	68.2	97.1
80	52.7	74.1	89
90	53	79.8	93
100	52.8	75.2	97.6

NILM: Non-intrusive load monitoring, DTA-LI: Decision tree algorithm-based load identification

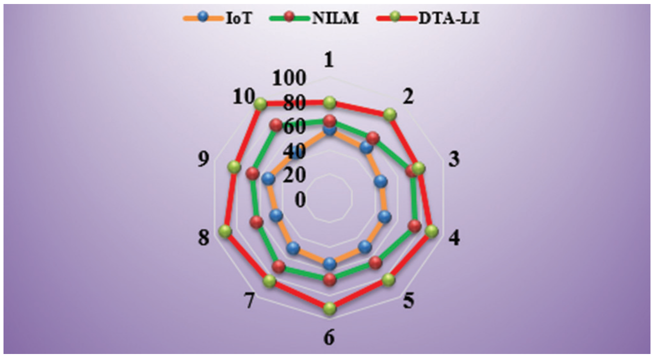

Figure 8: Systems transition in energy.

commonly utilized to moderate variations in renewable energy. The proposed method evaluated the electricity-saving rate, household energy consumption control, load-shedding management, efficiency, and system transition in energy.

4. Conclusion

The energy used in a home varies depending on the consumer's characteristics. The energy consumption profiles can be used to estimate the features of a home using the proposed framework. Smart meters forecast the number of residents, their task status, electrical appliances, and the number of bedrooms in residential buildings by analyzing univariate time series data. Hence, the technique can depend more on the events and length of the appliance used to make its determinations. Using a decision tree algorithm, they found that appliances' energy usage can track consumer behavior. With a low-cost power meter connector attached to the central control system, DTA-LI can determine the energy use of individual appliances. It is critical to know the characteristics of each home to implement energy-saving measures in housing developments. These clusters can be used to understand better the impact of each model's attributes on the overall power consumption patterns. Furthermore, they have demonstrated how the suggested technique can give relevant insights into the geodemographic level of a home by examining its time series relationships. The DTA-LI (DTA-LI) system enhances the electricity-saving rate by 95.1% and manages loads by 95.3% in the household**.** The application of these methods in developing forecasting processes for aggregated and disaggregated smart meter time series can be explored in future research.

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6. Conflicts of Interest

"The authors declare no conflicts of interest."

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