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Article

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Intelligent Energy Consumption For Smart Homes Using Fused Machine-Learning Technique

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Abstract: Energy is essential to practically all exercises and is imperative for the development of personal satisfaction. So, valuable energy has been in great demand for many years, especially for using smart homes and structures, as individuals quickly improve their way of life depending on current innovations. However, there is a shortage of energy, as the energy required is higher than that produced. Many new plans are being designed to meet the consumer's energy requirements. In many regions, energy utilization in the housing area is 30%–40%. The growth of smart homes has raised the requirement for intelligence in applications such as asset management, energy-efficient automation, security, and healthcare monitoring to learn about residents' actions and forecast their future demands. To overcome the challenges of energy consumption optimization, in this study, we apply an energy management technique. Data fusion has recently attracted much energy efficiency in buildings, where numerous types of information are processed. The proposed research developed a data fusion model to predict energy consumption for accuracy and miss rate. The results of the proposed approach are compared with those of the previously published techniques and found that the prediction accuracy of the proposed method is 92%, which is higher than the previously published approaches.

Keywords: Energy consumption; intelligent; machine learning; technique; smart homes; prediction

1 Introduction

The world's resources are being exhausted at an unsustainable rate and increasing temperatures and carbon dioxide emissions are strong indicators that global climate change is a severe problem. Sustainability has benefited the globe over the ages, and the global road to sustainability was hastened in 2015 with the acceptance of the sustainable development goals (SDGs). The 2030 Agenda for Sustainable Development [1], split into 17 SDGs, lays out a clear route for attaining global ecological, social, and economic sustainability. Working toward more maintainable procedures in industries, society, and everyday life requires accountable resource management. It entails both minimizing resource usage and employing resources wisely and sustainably. A well-managed energy scheme with a fresh energy mix is dangerous in mutual cases. This study focuses on two of the 17 SDGs: reasonable and clean energy, and maintainable cities and societies.

An energy management system (EMS) is a collection of hardware and software that measures, monitors, controls, and analyzes energy use. It has been used in various energy markets for more than a century. Many households had night thermostats in the early twentieth century, which might be regarded as the initial phase of EMS devices. However, the actual transformation started only in the early 1970s [2], when restricted energy supply and growing energy costs became a worry for citizens. Various firms, including General Electrics, Toshiba, Siemens, and Hitachi, embraced the evolution of EMS during this time, developing various products and solutions for the market.

Home energy management system (HEMS) has become critical amid the energy market and digitalization in recent years. The five key sections of HEMS have been, and continue to be, the ability for a customer to monitor, log, regulate, accomplish, and alarm energy use in their home from its inception. HEMS now features a variety of capabilities, from demand management to peak shaving and load control [3], because of fast technological advancement. Companies have improved their offers, and the sector has grown tremendously, with more than 50 companies now selling HEMS products throughout Europe [4].

Energy management optimization is a rising challenge of late. As buildings account for around 40% of the worldwide energy consumption, the E.U. proposes a 27% energy saving by 2030. The considerable rise in energy consumption poses several problems to energy safekeeping and the environment [5]. Increased energy efficiency was seen as an essential approach to handling the issues and encouraged the expansion of intelligent energy networks (IENs). IENs are used to illustrate a broad idea, including intelligent power grids, smart district heating (DH) networks, and intelligent natural gas systems. In recent years, IENs have evolved exceptionally quickly to satisfy the growing need for energy in a strong, flexible, environment-friendly, and cost-efficient way [6]. The essential components of IENs are smart energy meters, which are used to operate household machines. Traditional smart energy meters monitor energy consumption and communicate data between utilities and customers on energy consumption and working conditions. In other words, an essential characteristic of intelligent energy meters in IENs is two-way communication among meters and different strategies among meters [7].

The expectation of the heating, ventilation, and air conditioning is the critical factor for a residential area that is an essential perspective in anticipating the investigation of energy utilization. The idea of smart homes has been conceptualized since the 1990s. Smart homes can help or automate clients using artificial intelligence, distant home control, or home mechanization frameworks. The primary goal of a smart home is to improve the comfort of residents and simplify day-to-day life. Smart homes lead to a better quality of life by offering assistive technology and deploying fully mechanized control of appliances. This is accomplished by distinguishing the applicable human exercises, growing their robotization in home conditions, or utilizing far-off home control to give high solace levels, progress security, work with energy the executives, lessen ecological outflows, and save energy.

Energy monitors are a means to keep tabs on the inner workings of your home's energy system. They link to a home's electricity meter to display its energy consumption and information, making it more energy-efficient. Energy monitors provide various functions, ranging from identifying the energy use of appliances to creating individualized energy conservation advice.

Energy is an entity that describes its capability for several energy sources, such as energy potential, cinematic, chemical, and heat energy. It has been connected to several other concepts, such as clean energy, green energy, sustainable energy, and smart energy, in the last few years. People worry that the energy accessible for human consumption will be exhausted, which drives these terms related to new energy. Clean or green energy shows a low impact on the environment of energy consumption.

Smart energy is a larger concept than any of the above energy sources like clean energy or traditional energy. Intelligence can be referred to as the "Internet of Energy" model based on an intelligent energy generation concept or more, smart grid, smart consumption, and storage. Fig. 1 shows different components of smart energy.

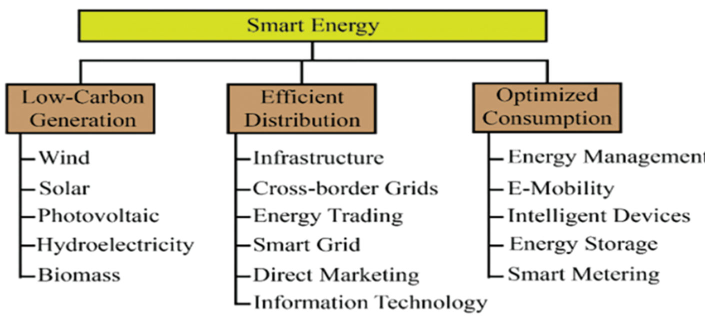

Figure 1: Components of smart energy

Fusion-based machine-learning (ML) techniques can be the prominent solution for developing an apparent solution while solving or developing an intelligent EMS for smart homes.

ML promotes machines recognizing and developing programs that make their actions and decisions more humane. It is effective for uncovering secret knowledge by learning from data recursively rather than being directly programmed. It approves computers to acquire data without human interaction and make decisions. It also allows computers or software on the way to analyze, forecast, and sort massive volumes of data and derive useful information. The learning process starts with data, guidelines, and assumptions to style improved decisions in the forthcoming.

Fusion may be centralized or decentralized. All sensor measurements are available during the fusion phase in the centralized model. Measurements of each sensor are fused in a decentralized fusion within a separate fusion model [8]. Data fusion, feature fusion, and decision fusion are three categories based on the stage of the fusion process. During data fusion, raw sensor data are fused, and the features and relationships of the information are known. These fused data are more refined than the original and have less data loss. The next step involves deriving the data characteristics to simplify the interpretation of data patterns. The objective is to strengthen decision-making and take the steps needed based on the available evidence.

2 Literature Review

Many researchers have worked on intelligent EMSs for smart homes. Some of the research studies are described in [9], and the binary particle swarm optimization (BPSO) strategy was developed. The fuzzy Mamdani derivation framework and BPSO fuzzy Sugeno inference system were developed for monitoring and booking electric burdens, respectively. These were developed on ten single-family lofts to control simple utilized machines, for example, washer, dryer, and so on, and occasionally used devices, for example, forced air system. Although the fuzzy logic method was being used for oversight, the BPSO used machines through low pinnacle hours. The indoor regulator set focuses on extending energy productivity. Cooling framework sets were set up as suggested by the predicted mean vote ordering strategy. When compared with the existing methods, the proposed method performs well in terms of energy consumption minimization. However, client solace is lost. A fuzzy regulator that uses aeration for detached cooling of the private structure has been planned.

Researchers opine that IoT and distributed computing have greatly advanced the smart home industry. They will fill in as empowering foundations for building up another age of system-driven home administrations where the taking of interesting home substances is dispersed on a metropolitan scale and combined [10].

The Misclassified Recall technique was created from the preprocessing phase of self-rectifying misclassified cases. Data transmission failures or defective instruments caused most misclassified events in energy data prediction. The former situation occurred regularly, whereas the errors caused by the latter can last for an extended period [11]. This study designed an improved version of the very fast decision tree, which learned from misclassified outcomes to filter noisy data while keeping the induced smart prediction models. Simulation experiments were performed on a dataset to forecast great appliance energy use in low-energy buildings. The results show better accuracy than the previously published studies [12,13].

Peng et al. [14] designed a system for developing home appliances using mixed-integer linear programming to save electricity costs by shifting load to off-peak times. The optimal profile reduced not only consumption, but also costs, peak power usage, and operational characteristics of smart equipment regulated by a power signal profile. Saleem et al. [15] developed a paradigm for managing electricity loads in smart home control, which included three parts: the user had to describe the load kind and load description, control reserve loads, and reveal a board for load management. Batool et al. [16] built a dynamic pricing system using the multiple knapsack technique, which saves money on power; consumer appliances were put on a variable peak pricing schedule day ahead. Based on load scheduling, several more techniques have been developed. A co-evolutionary particle swarm optimization technique was distinct [17] for families to cooperate for maximum benefits.

Smart buildings use information and communications technology (ICT) for their operations and controls. They increase occupants' comfort and efficiency by consuming less energy than conventional structures. Conventional buildings work independently, and intelligent buildings use ICT to link buildings to optimize their operations and efficiency. Intelligent buildings often allow operators and occupants to connect with the installation, giving access to operational activities and details. In addition, smart buildings can communicate to the grid, which is more and more necessary for utility demand. Although smart technology penetrates more in existing buildings, intelligent technology increases in all types of buildings [18].

Kim et al. [19] designed a framework to control homes with device sensors, given that homeowners aggregated energy data for all devices. A communal server is unified with various home setup devices inside a community, for example, security cameras. In addition, the Message Queuing Telemetry

Transport Protocol (MQTT) is compared with the Hypertext Transfer Protocol (HTTP) to see whether a procedure is competent in offering home management facilities. However, this framework does not use Big Data, which is essential for treating and examining large volumes of data from multiple home sensor networks.

Aliabadi et al. [20] developed a direct current (DC) distribution system with all domestic DC-based loads that communicate among each other, concentrating on Internet of Things (IoT)-based DC-powered homes. However, this idea of having smart DC-powered homes as a possible standby for AC power systems lacks common protocols and standards. IoT may address some challenges, which will give an assimilated platform for DC-driven technologies incompetent energy distribution.

Muneer et al. [21] delivered energy management data by addressing a variety of in-home display systems and automatic meter reading schemes. Smart homes could select TVs, smartphones, tablets, and computers based on the circumstances and suitable user interface. However, this design required a familiar user boundary for all home strategies to meet the demand for many shows. Mohammad et al. [22] suggested using an HEMS architecture based on a power line, which can display real-time data on home energy consumption and online entrance to device position via smart meter data, allowing consumers to control equipment remotely. This design was built on the conventional HTTP protocol. It does not support lightweight communication protocols such as MQTT, which must expand the system to serve various residential areas.

Tiwari et al. [23] presented a load scheduling challenge and characterized a load pledge problem. They suggested that the broad load consisting of the following is mere a cross-choice issue or a Markov decision problem with a single decision point. To address this problem, a reinforcement learning-based method was developed.

Papadimitrakis et al. [24] presented a structure for multi-inhabitant home energy consumption control based on mobility-aware resources. The proposed supportive game theory-based framework reduced total uncertainty for utility purposes. Many researchers suggested using a demand-side management simulation platform that incorporates dynamic distributed resource management [25–28]. Household appliances are simulated to implement a resource management strategy using a hybrid EMS.

Corno et al. [29], using smart meters as an example, conducted a literature review on the support of sustainable strategy for energy conservation, focusing on electronic feedback through smart meters. Enami et al. [30] developed a method for smartly managing energy consumption among customer needs and energy conservation based on sophisticated user motives and automatic device control. Asif et al. [31] recommended that the energy usage meter should be improved continuously based on the feedback.

Tab. 1 highlights the limitations in the previous work, including the lack of preprocessed data, decision-making, and fused ML [32]. Our method plays a vital role in facilitating the preprocessing layer that is used to process the data, decision making is used to facilitate decision power, and the fused ML is used to facilitate the autonomous and the robust decision-making in a better and efficient way.

Table 1: Comparison with the previous work

Authors	Preprocessing layer	Decision-making	Fused ML
Masum et al. [32]	No	No	Yes

3 Methodology

In this study, we propose a model to optimize energy consumption in smart homes. This model is proposed to overcome the limitation of high energy cost using fused ML to attain higher accuracy and more robust decision-making. Fig. 2 shows the training and validation phases of the proposed model. The training phase consists of five layers: IoT infrastructure, data acquisition layer, preprocessing layer, application layer, and performance layer. The data imported from the cloud is analyzed to determine the energy consumption in the validation phase.

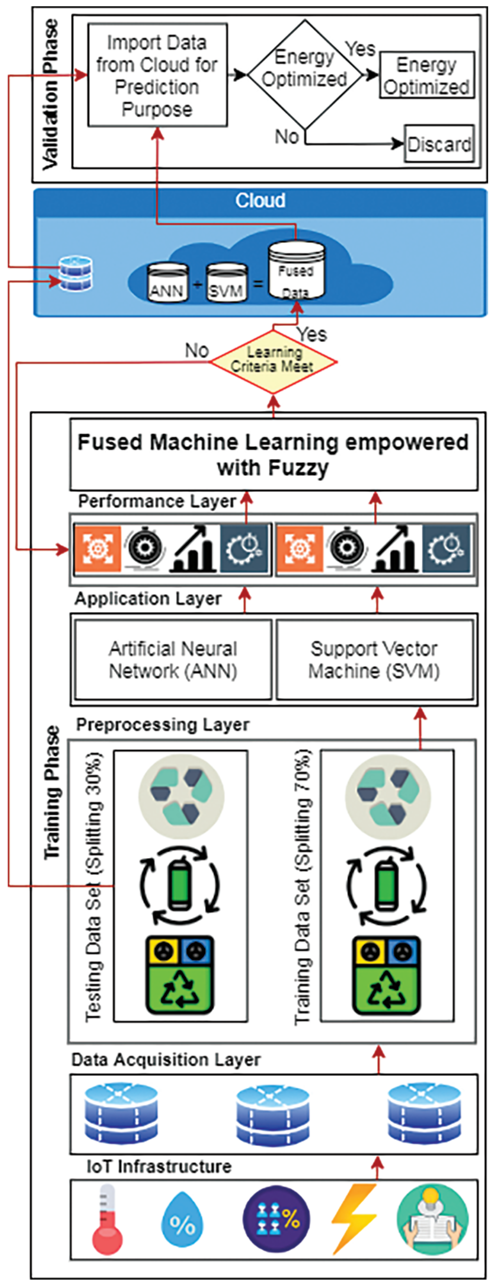

Figure 2: Proposed intelligent energy consumption for smart homes using fused ML technique

The IoT infrastructure has input parameters such as Day, Month, Year, Occupancy, Hours, Temperature, Humidity, Total Power, Pwt, Pac, and Category, the values of which are obtained from energy sensors, and these values are passed on to the data acquisition layer, which is known as raw data. The preprocessing layer mitigates the missing values using moving average and normalization. Then the preprocessed data is sent to the application layer, which is responsible for predicting energy consumption better and more efficiently. The predicted output is sent to the performance layer.

ML techniques [artificial neural networks (ANNs) and support vector machines (SVMs)] are applied in the application layer to monitor energy consumption. In ANNs, the three levels—input, hidden, and output—are described in the proposed model. Likewise, the backpropagation technique explained weight initialization, feedforward, backpropagation of error, weight, and bias updating. The activation function of each neuron in the hidden layer is f(x) = Sigmoid(x). The input sigmoid function and a hidden layer of the suggested model are written as

$$¥_{\mu} = \beta_1 + \sum_{k=1}^{\alpha} \left(\Omega_{k\mu} * \rho_k\right), \tag{1}$$

$$\oint_{v} = \frac{1}{1 + e^{-¥_{\mu}}} \text{ where } \mu = 1, 2, 3, \ldots, n. \tag{2}$$

The input taken from the output layer is

$$¥_{c} = \beta_2 + \sum_{\mu=1}^{n} \left(€_{\mu c} * \oint_{\mu}\right). \tag{3}$$

The output layer activation function is given as

$$\oint_{c} = \frac{1}{1 + e^{-¥_c}} \text{ where } c = 1, 2, 3, \ldots, €, \tag{4}$$

$$\mathbb{E} = \frac{1}{2} \sum_{c} \left(t_c - \oint_{c}\right)^2. \tag{5}$$

Eq. (4) represents backpropagation error, where t_c & $\boldsymbol{out}t_c$ is the desired output. In Eq. (5), the layer is written as the rate of change of weight for the production:

$$\Delta\Omega \propto -\frac{\partial\mathbb{E}}{\partial\Omega},$$

$$\Delta€_{\mu,c} = -\varepsilon\frac{\partial\mathbb{E}}{\partial€_{\mu,c}}. \tag{6}$$

After applying the chain rule, the above equation is written as

$$\Delta€_{\mu,c} = -\varepsilon\frac{\partial E}{\partial\oint_{c}} \times \frac{\partial\oint_{c}}{\partial¥_{c}} \times \frac{\partial¥_{c}}{\partial€_{\mu,c}}. \tag{7}$$

The value of weight change is obtained as

$$\Delta€_{\mu,c} = \varepsilon\left(\tau_c - \oint_{c}\right) \times \oint_{c}(1 - \oint_{c}) \times \left(\oint_{\mu}\right),$$

$$\Delta€_{\mu,c} = \varepsilon\xi_c\oint_{\mu}, \tag{8}$$

where

$$\xi_c = \left(\tau_c - \oint_{c}\right) \times \oint_{c}\left(1 - \oint_{c}\right).$$

By applying the chain rule, Eq. (8) can be written as

$$\Delta\Omega_{c,v} = \varepsilon\xi_{\mu}£_c$$

where

$$\xi_\mu = \left[\sum\nolimits_c \xi_c\left(€_{\mu,c}\right)\right] \times ʄ_\mu(1 - ʄ_\mu),$$

$$€^{+}_{\mu,c} = €_{\mu,c} + \lambda_F \Delta €_{\mu,c}. \tag{9}$$

The above equation is used for updating the weights between the output and hidden layers. The weights between the hidden and input layers are updated using

$$\Omega^{+}_{k,\mu} = \Omega_{k,\mu} + \lambda_F \Delta \Omega_{k,\mu}. \tag{10}$$

The output of the perdition layer will be sent to the performance layer, which will estimate the smart energy consumption based on accuracy and miss rate and that the learning conditions are met.

In SVMs, the equation of the line is

$$\text{ꓘ} = \text{н}\text{Ч} + \varsigma, \tag{11}$$

where н is the slope of a line and ς is the intersect. Therefore,

$$\text{н}\text{Ч} - \text{ꓘ} + \varsigma = 0.$$

Let $\bar{\text{ɫ}} = (\text{Ч}, \text{ꓘ})^{\mathrm{T}}$ and $\bar{\text{ɟ}} = (\text{н} - 1)$, then we have

$$\vec{\text{ɟ}}.\bar{\text{ɫ}} + \varsigma = 0. \tag{12}$$

The vector direction $\bar{\text{ɫ}} = (\text{Ч}, \text{ꓘ})^{\mathrm{T}}$ is written as

$$\text{ɟ} = \frac{\text{Ч}}{||\text{Ʈ}||} + \frac{\text{ꓘ}}{||\text{ɫ}||}, \tag{13}$$

where

$$||\text{ɫ}|| = \sqrt{\text{Ч}^2_{+}\text{ꓘ}^2_{+}\ldots\ldots\ldots..\text{ɫ}^2_{\zeta}}.$$

We know that

$$\cos(\theta) = \frac{\text{Ч}}{||\text{ɫ}||} \text{ and } \cos(\mu) = \frac{\text{ꓘ}}{||\text{ɫ}||}.$$

Eq. (13) can be rewritten as

$$\text{ɟ} = (\cos(\theta), \cos(\mu)),$$

$$\vec{\text{ɟ}}.\vec{\text{Ʈ}} = ||\text{ɟ}||\,||\text{Ʈ}||\cos(\theta),$$

$$\theta = \text{ύ} - \mu,$$

$$\cos(\theta) = \cos(\text{ύ} - \mu) = \cos(\text{ύ})\cos(\mu) + \sin(\text{ύ})\sin(\mu) = \frac{\vartheta}{||\text{ɟ}||}\frac{\text{Ч}}{||\text{ɫ}||} + \frac{\alpha}{||\text{ɟ}||}\frac{\text{ꓘ}}{||\text{ɫ}||} == \frac{\vartheta\text{Ч} + \alpha\text{ꓘ}}{||\text{ɟ}||\,||\text{ɫ}||},$$

$$\text{ɟ}.\text{ɫ} = ||\text{ɟ}||\,||\text{ɫ}||\left[\frac{\theta\text{Ч} + \alpha\text{ꓘ}}{||\text{ɟ}||\,||\text{ɫ}||}\right],$$

$$\vec{\text{ɟ}}.\vec{\text{ɫ}} = \sum_{i=1}^{\zeta} \text{ɟ}_i \text{ɫ}_i. \tag{14}$$

The dot product can be compared as the above for ζ-dimensional vectors

Let

$$B = M\left(\mathfrak{f}.t + \varsigma\right).$$

If sign (B) > 0, then it is appropriately classified, and if sign (B) < 0, then it is imperfectly classified.

Calculate f on a training dataset by dataset Π,

$$B_i = M_i\left(\mathfrak{f}.t + \varsigma\right).$$

The functional margin of the dataset Þ is given by

$$þ = \min_{i=1,\ldots,\text{Ƭ}} B_i.$$

Comparing hyperplanes with the largest þ will be complimentary selected. The objective is to find an optimal hyperplane, which requires finding the values of $\vec{\mathfrak{f}}$ and b of the optimal hyperplane.

The Lagrangian function is

$$\breve{A}\left(\mathfrak{f}, \varsigma, \mu\right) = \frac{1}{2}\mathfrak{f}.\mathfrak{f} - \sum_{i=1}^{\text{Ƭ}} \mu_i\left[M:\ \left(\mathfrak{f}.t + \varsigma\right) - 1\right],$$

$$\nabla_{\mathfrak{f}}\breve{A}\left(\mathfrak{f}, \varsigma, \mu\right) = \mathfrak{f} - \sum\nolimits_{i=1}^{\text{Ƭ}} \mu_i M_i t_i = 0, \tag{15}$$

$$\nabla_{\varsigma}\breve{A}\left(\mathfrak{f}, \varsigma, \mu\right) = -\sum\nolimits_{i=1}^{\text{Ƭ}} \mu_i M_i = 0. \tag{16}$$

From the above two equations, we obtain

$$\mathfrak{f} = \sum\nolimits_{i=1}^{\text{Ƭ}} \mu_i M_i T_i \text{ and } \sum\nolimits_{i=1}^{\text{Ƭ}} \mu_i M_i = 0. \tag{17}$$

By substituting the Lagrangian function Ă in the above equation, we obtain

$$\mathfrak{f}\left(\mu, \varsigma\right) = \sum_{i=1}^{\text{Ƭ}} \mu_i - \frac{1}{2}\sum_{i=1}^{\text{Ƭ}}\sum_{j=1}^{\text{Ƭ}} \mu_i\mu_j M_i M_j t_i t_j.$$

Thus,

$$\max_{\mu} \sum\nolimits_{i=1}^{\text{Ƭ}} \mu_i - \frac{1}{2}\sum\nolimits_{i=1}^{\text{Ƭ}}\sum\nolimits_{j=1}^{\text{Ƭ}} \mu_i\mu_j M_i M_j t_i t_j, \tag{18}$$

Subject to $\mu_i \geq 0, i = 1, \ldots, \text{Ƭ}, \sum\nolimits_{i=1}^{\text{Ƭ}} \mu_i M_i = 0$.

The inequality constraints extend the Lagrangian multipliers by using the Karush–Kuhn–Tucker conditions

$$\mu_i\left[M_i\left(\mathfrak{f}_i.t^* + \varsigma\right) - 1\right] = 0, \tag{19}$$

where t^* is the optimal point, μ is the positive value, and μ for the other points is ≈ 0. So,

$$M_i\left(\left(\mathfrak{f}_i.T^* + \varsigma\right) - 1\right) = 0. \tag{20}$$

The support vectors are close points to the hyperplane, as in Eq. (20),

$$\mathfrak{f} - \sum_{i=1}^{\mathfrak{T}} \mu_i M_i \mathrm{T}_i = 0,$$

$$\mathfrak{f} = \sum_{i=1}^{\mathfrak{T}} \mu_i M_i \mathrm{T}_{i.} \tag{21}$$

The value of ς is obtained using

$$M_i\left(\left(\mathfrak{f}_i.\mathrm{T}^* + \varsigma\right) - 1\right) = 0. \tag{22}$$

By multiplying M on by both sides of the above equation, we obtain

$$M_i^2\left(\left(\mathfrak{f}_i.\mathrm{T}^* + \varsigma\right) - M_i\right) = 0,$$

where $M_i^2 = 1$,

$$\left(\left(\mathfrak{f}_i.\mathrm{T}^* + \varsigma\right) - M_i\right) = 0,$$

$$\varsigma = M_i - \mathfrak{f}_i.\mathrm{T}^*. \tag{23}$$

Then,

$$\varsigma = \frac{1}{я}\sum_{i=1}^{я}\left(M_i - \mathfrak{f}.\mathrm{T}\right), \tag{24}$$

where я is the support vector number.

$$c\left(\mathfrak{f}_i\right) = \begin{bmatrix} +1 \text{ if } \mathfrak{f}.\mathrm{T} + \varsigma \geq 0 \\ -1 \text{ if } \mathfrak{f}.\mathrm{T} + \varsigma < 0 \end{bmatrix}. \tag{25}$$

The hyperplane is classified as class +1 (energy consumption found) and classified as −1 (energy consumption not found). So, the goal of the SVM algorithm is to predict a hyperplane that could disperse the data precisely.

The output of the application layer is forwarded to the performance layer to measure the accuracy and miss rate. The output of the performance layer is sent to the fusion-based approach using the fuzzy method. After the fuzzy inference system, if the learning criteria do not meet, it will be updated; if it is met, the output will be stored on a fused database on the cloud.

In the validation phase, the data will be imported from the cloud for prediction purposes, which checks whether the energy consumption is monitored or not. If no, the process will be discarded; if yes, the message will be displayed that energy consumption is monitored.

The proposed fuzzy logic-enabled decision-based fusion model is based on previous experience and rational thinking ability. The fuzzy logic controls the ambiguity and inaccuracy of data consumption effectively.

Fig. 3 shows the lookup diagram of the proposed energy consumption model that describes that when the performance of ANN is No and SVM is No, the energy consumption prediction of the proposed model will be No.

Fig. 4 shows the lookup diagram of the proposed energy consumption model that describes that when the performance of ANN is No and SVM is Yes, the energy consumption prediction of the proposed model will be Yes.

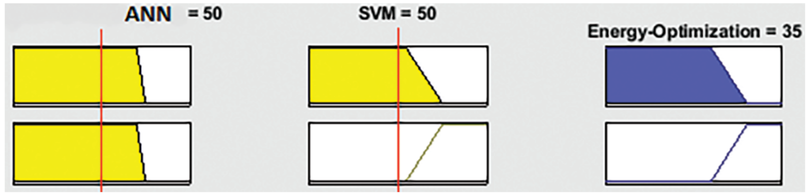

Figure 3: Lookup diagram of the proposed energy consumption model

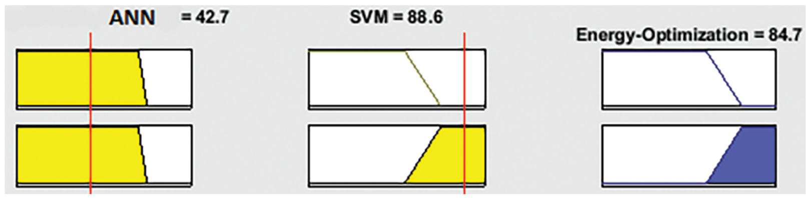

Figure 4: Lookup diagram of the proposed energy consumption model

Fig. 5 shows the lookup diagram of the proposed energy consumption model that describes that when the performance of ANN is Yes and SVM is Yes, the energy consumption prediction of the proposed model will be Yes.

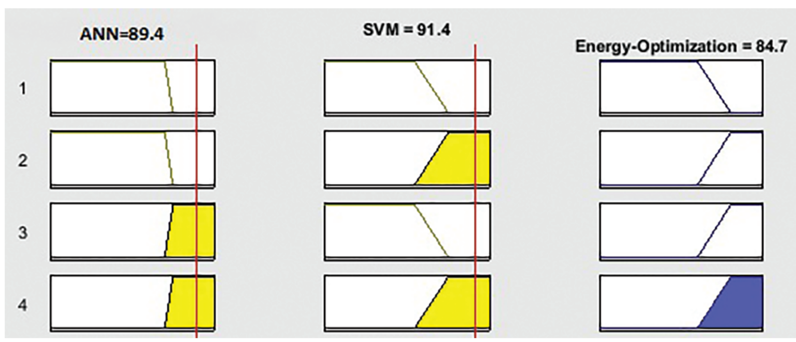

Figure 5: Lookup diagram of the proposed energy consumption model

From the above, we understand the following criteria:

R1 = “Energy consumption prediction is Yes, if ANN is Yes and SVM is Yes.”

R2 = “Energy consumption prediction is Yes, if ANN is Yes and SVM is No.”

R3 = “Energy consumption prediction is Yes, if ANN is No and SVM is Yes.”

R4= “Energy consumption prediction is No, if ANN is No and SVM is No”

Fig. 6 shows the graphical representation of energy consumption prediction. It clearly shows that the energy consumption prediction is bad if SVM is 0–50 and ANN 0–50. The energy consumption prediction is satisfactory if SVM is 50–60 and ANN is 50–80. The energy consumption prediction is good if SVM is 60–100 and ANN is 80–100.

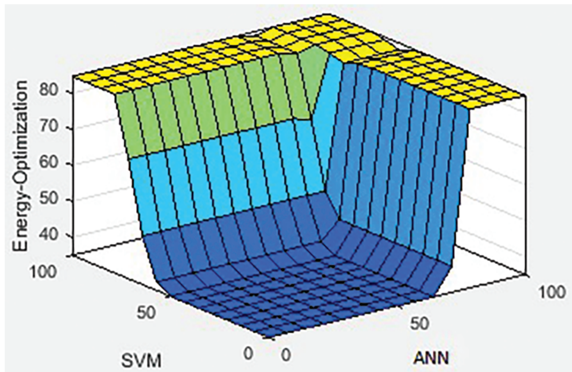

Figure 6: Rule surface of the proposed energy consumption model

4 Simulation Results

This study aims to predict energy consumption in a smart home using a fusion-based approach. The proposed method is used for an energy dataset of 22802 samples collected for UCI Machine Learning. The dataset is divided into 70% (15861) training and 30% (6763) tests. The simulation results for predicting energy consumption are obtained using ANNs and SVMs, which gives excellent accuracy and miss rate.

SVM and ANN approaches are being used on the 22802 sets of records; the dataset is divided into training (15961 samples; 70%) and training and validation (6841 samples; 30%). To determine the performance, we used various formulas, as given below:

$$\text{Sensitivity} = \frac{\sum \text{True Positive}}{\sum \text{Condition Positive}}, \tag{26}$$

$$\text{Specificity} = \frac{\sum \text{True Negative}}{\sum \text{Condition Negative}}, \tag{27}$$

$$\text{Accuracy} = \frac{\sum \text{True Positive} + \sum \text{True Positive}}{\sum \text{Total Population}}, \tag{28}$$

$$\text{Miss Rate} = \frac{\sum \text{False Negative}}{\sum \text{Condition Positive}}, \tag{29}$$

$$\text{Fallout} = \frac{\sum \text{False Positive}}{\sum \text{Condition Negative}}, \tag{30}$$

$$\text{Likelihood Positive Ratio} = \frac{\sum \text{True Positive Ratio}}{\sum \text{False Positive Ratio}}, \tag{31}$$

$$\text{Likelihood Negative Ratio} = \frac{\sum \text{True Positive Ratio}}{\sum \text{False Positive Ratio}}, \tag{32}$$

$$\text{Positive Predictive Value} = \frac{\sum \text{True Positive}}{\sum \text{Predicted Condition Positive}}, \tag{33}$$

$$\text{Negative Predictive Value} = \frac{\sum \text{True Negative}}{\sum \text{Predicted Condition Negative}}. \tag{34}$$

Tab. 2 shows the prediction of energy consumption by the proposed system using SVM. During training, a total of 15861 samples are used, which are divided into 15261 and 600 positive and negative samples, respectively. A total of 13700 true positives are successfully predicted, and no energy consumption is identified, but 1561 records are mistakenly predicted as negatives, indicating energy consumption. Similarly, 600 samples are obtained, with negative showing energy consumption and positive showing no energy consumption. With 580 samples correctly identified as negative showing energy consumption and 20 samples inaccurately predicted as positive, indicating no energy consumption despite the existence of energy consumption.

Table 2: Proposed model training during the prediction of energy consumption (SVM)

	Total number of samples (15861)	Result (output)	
Input	Expected output	Predicted positive	Predicted negative
		True positive (T.P.)	False positive (F.P.)
	15261 Positive	13700	1561
		False negative (F.N.)	True negative (TN)
	600 Negative	120	580

Tab. 3 shows the prediction of energy consumption by the proposed system using SVM. A total of 6763 samples are used during training, divided into 6538 and 225 positive and negative samples, respectively; 5618 true positives are successfully predicted, and no energy consumption is identified, but 920 records are mistakenly predicted as negatives, indicating energy consumption. Similarly, 225 samples are obtained, with negative showing energy consumption and positive showing no energy consumption. With 217 samples correctly identified as negative showing energy consumption and 8 samples inaccurately predicted as positive, indicating no energy consumption despite the existence of energy consumption.

Table 3: Proposed model validation during the prediction of energy consumption (SVM)

	Total number of samples (6763)	Result (output)	
Input	Expected output	Predicted positive	Predicted negative
		True positive (T.P.)	False positive (F.P.)
	6538 Positive	5618	920
		False negative (F.N.)	True negative (TN)
	225 Negative	8	217

Tab. 4 shows the prediction of energy consumption by the proposed system using ANN. During training, a total of 15961 samples are used, which are divided into 15261 and 700 positive and negative samples, respectively; 13864 true positives are successfully predicted, and no energy consumption is identified, but 1397 records are mistakenly predicted as negatives, indicating energy consumption. Similarly, 700 samples are obtained, with negative showing energy consumption and positive showing no energy consumption. 593 samples were identified adequately as negative, indicating energy consumption, and 107 samples were inaccurately predicted as positive, indicating no energy consumption despite the existence of energy consumption.

Table 4: Proposed model training during the prediction of energy consumption (ANN)

	Total number of samples (15961)	Result (output)	
Input	Expected output	Predicted positive	Predicted negative
		True positive (T.P.)	False positive (F.P.)
	15261 Positive	13864	1397
		False negative (F.N.)	True negative (TN)
	700 Negative	107	593

Tab. 5 shows the prediction of energy consumption by the proposed model using ANN. During training, a total of 6841 samples are used, which are divided into 6538 and 303 positive and negative samples, respectively; 5741 true positives are successfully predicted, and no energy consumption is identified, but 797 records are mistakenly predicted as negatives, indicating energy consumption. Similarly, 303 samples are obtained, with negative showing energy consumption and positive showing no energy consumption. With 224 samples correctly identified as negative, showing energy consumption, and 79 samples inaccurately predicted as positive, indicating no energy consumption despite energy consumption.

Table 5: Proposed model validation during the prediction of intrusion (ANN)

	Total number of samples (6841)	Result (output)	
Input	Expected output	Predicted positive	Predicted negative
		True positive (T.P.)	False positive (F.P.)
	6538 Positive	5741	797
		False negative (F.N.)	True negative (TN)
	303 Negative	79	224

Tab. 6 shows that the proposed model learning technique performs well in terms of accuracy, sensitivity, specificity, miss rate, and precision during the training and validation phase using SVM. It shows that the proposed model provides the values of 0.894, 0.897, 0.828, 0.106, and 0.991 throughout training, respectively. During validation, the proposed model provides 0.862, 0.859, 0.964, 0.138, and 0.998 for accuracy, sensitivity, specificity, miss rate, and precision, respectively.

In addition, the proposed system predicts the values of 0.171, 5.245, 0.128, and 0.270 during training and 0.035, 124.628, 0.143, and 0.190 during validation for fall out, positive likelihood ratio, likelihood negative ratio, and negative predictive value, respectively.

Table 6: Performance evaluation of the proposed energy consumption model in training and validation using different statistical measures (SVM)

SVM	Accuracy	Sensitivity TPR	Specificity TNR	Miss rate (%) FNR	Fallout FPR	LR+	LR−	PPV (precision)	NPV
Training	0.894	0.897	0.828	0.106	0.171	5.245	0.128	0.991	0.270
Validation	0.862	0.859	0.964	0.138	0.035	124.628	0.143	0.998	0.190

Tab. 7 shows the learning technique performance for accuracy, sensitivity, specificity, miss rate, and precision throughout the training and validation phase by the proposed system using ANN. It clearly shows that the proposed model gives 0.905, 0.908, 0.847, 0.054, and 0.992 for accuracy, sensitivity, specificity, miss rate, and precision during training, respectively. And provides 0.873, 0.878, 0.761, 0.127, and 0.988 for accuracy, sensitivity, specificity, miss rate, and precision during validation, respectively. In addition, more statistical measures such as fall out likelihood positive ratio, likelihood negative ratio, and negative predictive value are added to predict the values.

Table 7: Performance evaluation of the proposed energy consumption model in training and validation using different statistical measures (ANN)

ANN	Accuracy	Sensitivity TPR	Specificity TNR	Miss rate (%) FNR	Fallout FPR	LR+	LR−	PPV (precision)	NPV
Training	0.905	0.908	0.847	0.054	0.152	5.973	0.0637	0.992	0.298
Validation	0.873	0.878	0.761	0.127	0.238	3.689	0.166	0.988	0.219

Tab. 8 shows that out of 13 tests, only one is opposite to the proposed model and human-based decision, indicating the accuracy level of 0.923 of the proposed system. Tab. 9. compares the performance of the proposed system using SVM and ANN and shows that the accuracy and miss rate are 0.862 and 0.138 using SVM and are 0.873 and 0.127 using ANN, respectively. The results demonstrate that the accuracy is 0.923 and the miss rate is 0.077 using the proposed fusion-based approach.

Table 8: Fusion results of the proposed smart energy consumption system empowered with fussed ML techniques (SVM and ANN)

S. NO.	SVM	ANN	The proposed (SID-FLFEF-ML)	Human expert decision of SID-FLFEF-ML	Probability of correctness	Probability of errors
1	89.4 (Yes)	91.4 (Yes)	84.7 (Yes)	Yes	1	0
2	28.1 (No)	41.1 (No)	50 (No)	Yes	1	0
3	27.1 (No)	24.1 (No)	50 (No)	No	1	0
4	27.1 (No)	24.1 (No)	50 (No)	No	1	0
5	27.1 (No)	24.1 (No)	50 (No)	No	1	0
6	27.1 (No)	24.1 (No)	50 (No)	No	1	0

(Continued)

Table 8: Continued

S. NO.	SVM	ANN	The proposed (SID-FLFEF-ML)	Human expert decision of SID-FLFEF-ML	Probability of correctness	Probability of errors
7	28.1 (No)	71.1 (Yes)	84.7 (Yes)	Yes	1	0
8	28.1 (No)	71.1 (Yes)	84.7 (Yes)	Yes	1	0
9	28.1 (No)	71.1 (Yes)	84.7 (Yes)	Yes	1	0
10	28.1 (No)	71.1 (Yes)	84.7 (Yes)	Yes	1	0
11	91.3 (Yes)	71.1 (Yes)	84.7 (Yes)	Yes	1	0
12	91.3 (Yes)	71.1 (Yes)	84.7 (Yes)	Yes	1	0
13	91.3 (Yes)	71.1 (Yes)	50 (No)	Yes	0	1

Table 9: Comparison of performance of the proposed system using SVM and ANN algorithms

SVM	Accuracy	0.862
	Miss rate	0.138
ANN	Accuracy	0.873
	Miss rate	0.127
Fusion-based ML approach	Accuracy	0.923
	Miss rate	0.077

5 Conclusion

This study opens new opportunities for intelligent energy consumption in IoT and cloud platforms. The proposed model consisted of training and validation phases for building a smart energy consumption model to support different stakeholders through their respective rights. The proposed model empowers the users to monitor and govern devices remotely. The proposed model uses the data fusion approach for the enhanced prediction of energy consumption in terms of accuracy and miss rate. Simulation results are compared with the previously published results. The prediction accuracy of the proposed method is 92.3%, which is higher than the previous research studies.

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