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RESEARCH ARTICLE

An Innovative Machine Learning Technique for the Prediction of Weather Based Smart Home Energy Consumption

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ABSTRACT The prediction of energy consumption plays a significant role in energy conservation and reducing the cost of power generation, to improve energy sustainability and economic stability. Current studies show an increased interest in the application of Machine Learning algorithms to forecast energy utilisation in smart homes. The performance of these Machine Learning algorithms is evaluated using accuracy algorithms. The process of manually selecting best-performing Machine Learning algorithms is still very challenging for data analysts and decision makers because the algorithms might not work well in a different use case or data-set. To address this, we propose a decision algorithm model using machine learning based data mining and picture fuzzy operators. First, Machine Learning algorithms are trained and tested to predict energy consumption of smart home appliances with respect to the weather information. Second, score values of Lasso Regression are used to understand the patterns and features of weather information for smart house micro-climate. We then propose a decision matrix using fuzzy operators to aggregate Machine Learning algorithms, prior to ranking using a score function. Finally, the electricity consumption of appliances as well as total energy consumed in the smart home is provided in Kilowatts (KW).

INDEX TERMS Appliances, decision support too, energy consumption prediction, machine learning, smart home.

I. INTRODUCTION

Effective Energy consumption is believed a leading cause of carbon emissions, almost 80%, according to recent reports [1]. This leads the major cause of environmental instability and climate change. Higher consumption of fossil fuels is caused the extreme weather conditions and their associated impacts on climate change are big hurdles in achieving Sustainable Development Goals (SDGs). Efficient and clean energy accessibility and tackling emissions are the two main groups of 17-point SDGs roadmap that United Nations (UN) has set out to achieve by 2030 [2]. In the United States (US) alone, 30% of the total 100% energy is wasted by residential and commercial sectors [3]. Human survival is significantly affected by the climate conditions. There has been a rising concern that the weather variations might be severe in the coming days if prior measures are not planned and carried out. Current variations in the temperature, across the world, are seriously increasing the energy consumption [4]. The impact of weather changes is even more evident in the residential sectors where operational carbon emissions are associated with the consumption of smart house appliances such as lighting, heating, cooling, plug devices (mobiles, computers, microwave). Therefore, reducing the consumption of

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above-mentioned devices can mitigate the carbon emission at national level. Moreover, residential sector is more weather vulnerable than other industrial sectors. This is one of the main reasons that residential sector is consuming at least 30% of the total worldwide energy [5], [6].

The information management platforms such as Smart Homes Energy Management Systems (SHEMs) are widely deployed to analyse, visualise and to monitor energy usage patterns of the household appliances. This is mainly possible by using integrated wireless sensors in the smart home appliances to collect the relevant data. These datasets, are then, used to get useful insights of the hidden patterns of interest to take data-driven future decisions related to energy management. Smart home's technologies such as big data tools, data analysis and data visualisation techniques play significant role to process large amount of multi-variant datasets [7]. Smart technologies enabled energy optimisation helps to reduce energy wastage which ultimately, leads to more sustainable buildings and environment. Current literature also demonstrates the effective use of residential energy feedback technologies to implement energy saving strategies as well as to maintain energy demand and response [8], [9]. One such example is of In-Home Displays (IHDs), which are used in large number of experimental studies to understand the use of energy using data visualization techniques [10] in the homes. However, they only provide whole-home energy feedback and clearly lack the capabilities of energy control to use it effectively [8]. Literature also suggests that such smart displays are only useful to realise energy demand and response to shift energy usage from peak-time to off-peak times. However, up to 20% of energy could be saved if they are integrated with load-monitors and smart appliances. Few studies, in the past, used a single interface for various appliances, for instance, Residential Electricity Cost Speedometer (RECS) which only displays present cost per hour for different appliances [11]. Their major drawback is that they are mostly focused on demand shifting potential instead of energy optimisation strategies. Another example is of "Southern California Edison" who worked on smart appliances and assessed the behaviour of appliances for demand side responses and also shared the various strategies to cope with these responses, published in [8].

The targets have been set from the United Nations to mitigate the emissions from residential buildings by 2050 [12]. The concept of energy saving, and climate neutral houses and buildings is a global challenge. For this, energy saving research is encouraging to sustainable urban development. Existing building net zero greenhouse gas emission and energy saving plans and guidelines are mainly designed at reducing electricity consumption [13], [14].The European Union (EU) has also planned to move from "zero-energy buildings to a zero-emission building" goal by 2030. This target has been officially started to implement into the buildings sector. [15].

Energy consumption is directly linked to the change in weather conditions in particular areas. For instance, the amount of energy that is used in a house is dependent on the contextual information of weather such as climate conditions, temperature and humidity level. These are some of the factors that ultimately has influence on the consumption of energy and caused seasonal variation in demand and supply stability. Prediction of energy consumption on certain locations is predominantly linked with the weather terms. However, weather conditions, sometimes, are very unpredictable. This unpredictability in weather conditions causes variations in the actual energy consumption and the predicted ones, leaving the energy networks more vulnerable. Furthermore, renewable energy devices that are installed in the houses as well as the electrification of the energy systems are also considered big causes of temperature variations in the houses [16]. The accurate calculation of weather risk factor in the modelling of energy system used the average small amount (1-3 years) of data. The impact of weather behaviour is important and has been recorded for the future designing and modelling of energy system. The electricity consumption behaviour of electrical appliances plays vital role for the energy management of smart home. Therefore, accurate and timely prediction of electrical loads can play significant role to save smart home energy and can also reduce the financial burden on residents. Similarly, this timely prediction can also reduce the load and financial burden on national power grid improving in the stability of power system [17].

According to the latest study published by United Kingdom Office for National Statistics [18] on climate change impacts, living standards, families, and residential houses or households. It was observed houses and households are the main sources to emit greenhouse gases in the UK reporting 26%. In 2020, It was observed that Northern Ireland produced maximum domestic emissions per capita following the London for highest emissions per square kilometre. It was examined that about a third of adults (34%) made no explicitly changes in their lifestyle to mitigate the emission. According to a survey [19] on lifestyle and energy consumption and changing in lifestyle can bring energy efficiency in the houses. The survey stated that a small social experiment on 77% of adults was conducted and observed that lifestyle can reduce energy consumption as well as mitigate the emissions. Therefore, both factors (Climate change and lifestyle) play critical role for the saving of energy consumption in the residential buildings.

In our paper, we examine the following research questions: how external weather and climate change influences the energy consumption on smart houses. Which machine learning technique accurately predict short-term energy consumption using weather data with higher accuracy. How to automate the selection process of best machine learning model. Therefore, the objective of this research work is two-folded; **first** is to find the best Machine Learning (ML) algorithms for the forecasting of smart home energy consumption to enhance energy efficiency in smart homes using weather data. The accurate prediction is vital to reduce the home's energy consumption while improving the living comfort. However, because of the multiple types of ML algorithms and the minimum information about accuracy of algorithms, it is challenging for the analysts and decision makers to accurately select the best algorithms for appliances energy consumption. Therefore, the **second** objective is imperative to develop a technique for selecting the best ML algorithm using the score values and fuzzy operators understanding the appliances electricity consumption patterns and features. The overall flow chart of proposed model can be seen in the Figure 1.

The main contributions of this research work are as follows:

- An approach for forecasting of smart home appliances energy consumption using ML algorithms.
- A methodology to find the score values exploring the pattern and features of home appliances data.
- Fuzzy aggregation operators are developed.
- Design of decision framework for the selection of best ML algorithm using fuzzy operators.

The rest sections of this research article are organized as follows; Section II will discuss related literature surveys in the research area of smart homes technology, energy consumption, weather impact in electricity consumption and ML techniques in energy forecast and fuzzy decision making sets. Section III will explain the implementation of ML algorithms. Section IV will describe the design of decision matrix. Section V will discuss the aggregation operators. Section VI explains experiment results and discussion of the main ML techniques and decision matrix, while the last Section VII will conclude the work and developed model along the future work of forecasting models.

II. RELATED WORK AND RESEARCH GAP

A. ENERGY CONSUMPTION PREDICTION MODELS

The assessment and forecasting of energy consumption are essentials for improving energy efficiency and environmental management for smart houses. In this literature review section, the importance of energy consumption prediction, impact of weather information, energy efficiency, and intelligent decision-making algorithms have been reviewed. Intelligent consumption prediction and decision-making algorithms such as machine learning and fuzzy logic based intelligent techniques have been designed and implemented to forecast energy consumption data to enhance and promote energy efficiency and management for smart buildings [20], [21], [22], [23], [24], [25], [26].

Reference [27] compared and evaluated the ML models; Support Vector Regression, Backward Propagation Neural Network, Extreme Learning Machine, And Adaptive Network based Fuzzy Inference System for predicting energy consumption for smart buildings. Reference [28] proposed a hybrid deep learning technique for the forecasting of household energy consumption. The hybrid model is a recipe of Long Short Term Memory (LSTM) and Stationary Wavelet Transform (SWT). In this model, experiments were performed on households' energy consumption dataset and observed the LSTM model enhances the accuracy and performance of energy consumption prediction. Reference [29] investigated stochastic learning models which are "Conditional Restricted Boltzmann Machine" (CRBM) and "Factored Conditional Restricted Boltzmann Machine" (FCRBM). They examined that "Factored Conditional Restricted Boltzmann Machine (FCRBM)" performed well on energy consumption dataset with better energy consumption prediction accuracy and outperformed the other ML models for instance ANN, SVM, RNN. Reference [30] developed CNN-based WaveNet technique for short term forecasting and handling noisy data of energy appliances. They concluded that WaveNet performed well on short term prediction of electric loads for households. They also explored the correlation between electric load and temperature using transfer learning. Reference [31] developed ensemble learning model to predict energy demand for residential buildings. They integrated extreme learning machine, extreme gradient boosting, and support vector regression based linear regression. This article [32], [33] proposed an approach to predict residential household electricity consumption using human behaviour. In [34] authors used statistical models (ARIMA and TBATS) for energy consumption prediction for household.

The significance of predicting weather pattern and behaviour and the impact of this pattern has shown more severe consequences into the energy system. This review is particularly aimed to investigate the energy consumption pattern of smart homes appliances, and also investigate the impact of changing weather pattern on energy consuming appliances of smart homes [35]. Reference [36] explored the relationship between temperature and electricity consumption demand to observe the impact of climate change on energy consumption pattern at national and international level. They concluded that there is a certain surge in the energy consumption loads due to the impact of weather. This article [37] studied the short term (5 minutes) variational impact of weather on energy consumption data which was obtained from residential households. Results concluded that there is a vulnerable relation between the weather and energy consumption behaviour of the appliances. Reference [38] explored the significance and impact of local weather data, load data, and occupancy data on energy consumption using "Quasi-Newton Backpropagation" (QNBP), "Levenberg Marquardt Back-propagation" (LMBP), "Bayesian regularization" (BR), and "Scaled conjugate gradient" (SCG). They come with the results that the behaviour of temperature was normal during the winter. Reference [39] Investigated the increasing abnormal behaviour of weather on buildings energy supply and demand. The author explored the various models to develop a framework which was implemented to calculate the severe impact of irregular

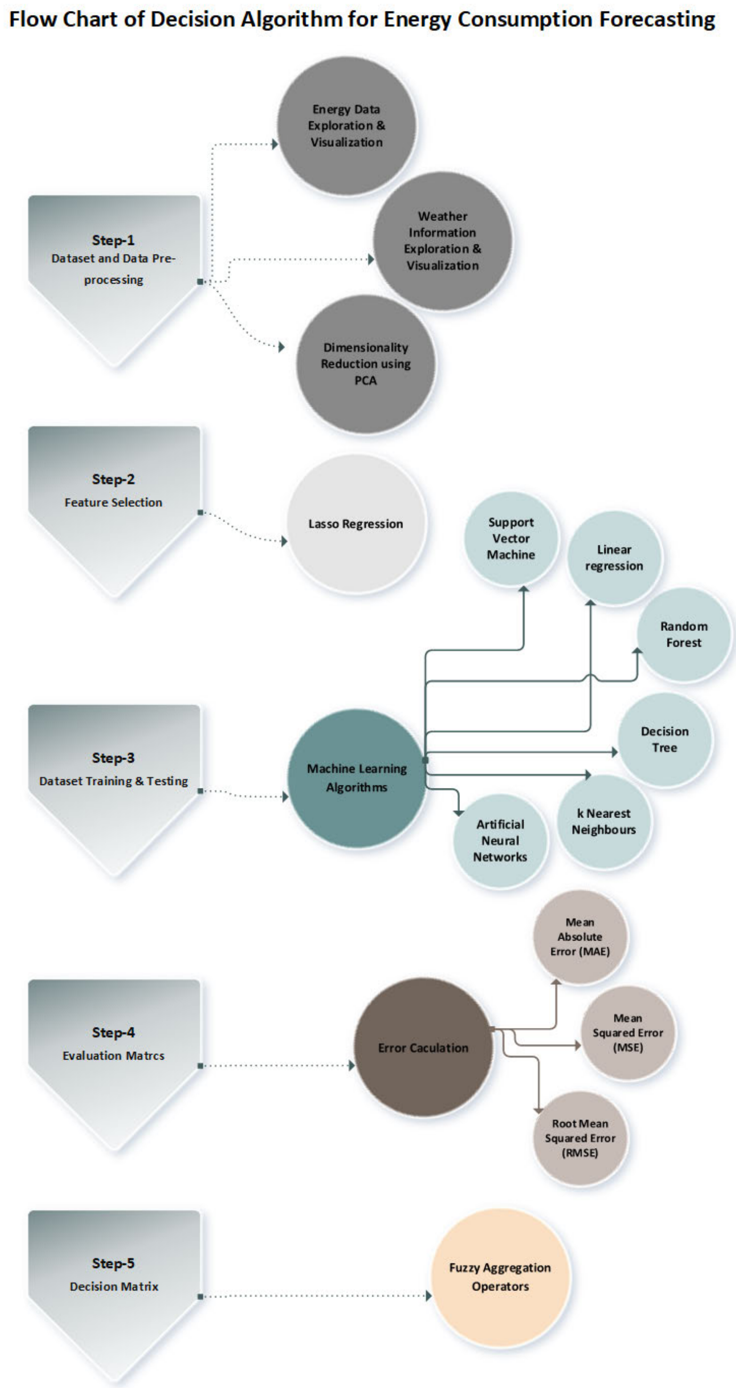

FIGURE 1. Flow chart of proposed model.

weather performance on electricity generation and consumption and discussed the Britain's case study of power system to establish the applicability of the framework. Reference [40] calculated the impact of weather (temperature) variation on electricity consumption at national level. They conducted to examine the correlation between the impact of weather situation and the electricity consumption of appliances. This study concluded that electricity consumption increases when there is an increase in temperature during the day times in summer. Additionally, the fall in winter temperatures could also affect the electricity consumption [41]. Another study [42] that looked into how climate change would affect patterns of electricity consumption in Spain came to the conclusion that electricity consumption increased as the temperature increased in summer day.

In this research work, We use the smart house dataset to observe the impact of contextual conditions such as weather information and appliances usage and their behaviour on the overall energy consumption of the house. This study predicted the next two days' energy consumption data using six machine learning models, including linear regression, decision trees, k-nearest neighbours regression, support vector regression, random forests, and neural networks. Furthermore, the outputs of these ML models are evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE).

B. BASIC CONCEPTS FOR PICTURE FUZZY SET

Decision-making challenges are prevalent in a wide variety of disciplines, including technology, finance, and marketing. Typically, it has been thought that all data on alternate access is stored in the form of discrete integers. Since, in real-world situations, it is critical to manage the imprecision and uncertainty inherent in data. When it comes to select anyone, there are supposed to be three possible responses, namely yes, no, and refusal. However, first most sophisticated response is "refusal," which conventional "fuzzy sets" [43] and "intuitionistic fuzzy sets" (IFSs) [44] may not accurately represent. To solve these issues, Cuong suggested the "picture fuzzy set" (PFS) [45], [46]. In PFS, each element in the set has diverse degrees of "positive membership degree" (PMSD), "neutral membership degree" (N_uMSD) and "negative membership degree" (N_gMSD) with values ranging from [0, 1].

This portion of the study discusses some important notions linked with PFSs over the set X.

Definition 1 [45], [46]: A "picture fuzzy set" (PFS) in X is characterized as

$$\chi = \{\langle \breve{\Upsilon}, \eta_\chi(\breve{\Upsilon}), \rho_\chi(\breve{\Upsilon}), \aleph_\chi(\breve{\Upsilon}) | \breve{\Upsilon} \in X \rangle\} \tag{1}$$

where $\eta_\chi(\breve{\Upsilon}), \rho_\chi(\breve{\Upsilon}), \aleph_\chi(\breve{\Upsilon}) \in [0,1]$, such that $0 \le \eta_\chi(\breve{\Upsilon}) + \rho_\chi(\breve{\Upsilon}) + \aleph_\chi(\breve{\Upsilon}) \le 1$ for all $\breve{\Upsilon} \in X$. $\eta_\chi(\breve{\Upsilon}), \rho_\chi(\breve{\Upsilon}), \aleph_\chi(\breve{\Upsilon})$ denote PMSD, N_uMSD and N_gMSD respectively for some $\breve{\Upsilon} \in X$.

We denote this pair as $\gamma^\zeta = (\eta_{\gamma^\zeta}, \rho_{\gamma^\zeta}, \aleph_{\gamma^\zeta})$, over the span of this investigation, and designated as PFN under the circumstances $\eta_{\gamma^\zeta}, \rho_{\gamma^\zeta}, \aleph_{\gamma^\zeta} \in [0,1]$ and $\eta_{\gamma^\zeta} + \rho_{\gamma^\zeta} + \aleph_{\gamma^\zeta} \le 1$.

When implementing PFNs to actual situations, it is crucial to categorize them. In this case, the "score function" (SF) corresponds to the PFN $\gamma^\zeta = (\eta_{\gamma^\zeta}, \rho_{\gamma^\zeta}, \aleph_{\gamma^\zeta})$ is given as,

Definition 2 [47]: Let $\gamma^\zeta = \left(\eta_{\gamma^\zeta}, \rho_{\gamma^\zeta}, \aleph_{\gamma^\zeta}\right)$ be PFN, then SF $\breve{\eta}^\beth(\gamma^\zeta)$ and accracy function (AF) $\hat{L}(\gamma^\zeta)$ for PFN are defined as follows:

$$\breve{\eta}^\beth(\gamma^\zeta) = \frac{1 + \eta_{\gamma^\zeta} - \aleph_{\gamma^\zeta}}{2}, \quad \breve{\eta}^\beth(\gamma^\zeta) \in [0,1], \tag{2}$$

$$\hat{L}(\gamma^\zeta) = \eta_{\gamma^\zeta} - \aleph_{\gamma^\zeta}, \quad \hat{L}(\gamma^\zeta) \in [-1,1]. \tag{3}$$

We will now review the operational principles for combining PFNs.

Definition 3 [48]: Consider $\gamma^\zeta{}_1 = \langle \eta_1, \rho_1, \aleph_1 \rangle$ and $\gamma^\zeta{}_2 = \langle \eta_2, \rho_2, \aleph_2 \rangle$ are the PFNs, $\beth > 0$ then

$$\gamma^\zeta{}_1^c = \left\langle \aleph_1, \rho_1, \eta_1 \right\rangle \tag{4}$$

$$\gamma^\zeta{}_1 \vee \gamma^\zeta{}_2 = \left\langle max\{\eta_1, \eta_2\}, min\{\rho_1, \rho_2\}, min\{\aleph_1, \aleph_2\} \right\rangle \tag{5}$$

$$\gamma^\zeta{}_1 \wedge \gamma^\zeta{}_2 = \left\langle min\{\eta_1, \eta_2\}, max\{\rho_1, \rho_2\}, max\{\aleph_1, \aleph_2\} \right\rangle \tag{6}$$

$$\gamma^\zeta{}_1 \oplus \gamma^\zeta{}_2 = \left\langle \eta_1 + \eta_2 - \eta_1\eta_2, \rho_1\rho_2, \aleph_1\aleph_2 \right\rangle \tag{7}$$

$$\gamma^\zeta{}_1 \otimes \gamma^\zeta{}_2 = \left\langle \eta_1\eta_2, \rho_1 + \rho_2 - \rho_1\rho_2, \aleph_1 + \aleph_2 - \aleph_1\aleph_2 \right\rangle \tag{8}$$

$$\beth\gamma^\zeta{}_1 = \left\langle 1 - (1-\eta_1)^\beth, \rho_1^\beth, \aleph_1^\beth \right\rangle \tag{9}$$

$$\gamma^\zeta{}_1^\beth = \left\langle \eta_1^\beth, 1 - (1-\rho_1)^\beth, 1 - (1-\aleph_1)^\beth \right\rangle \tag{10}$$

Definition 4 [47]: Consider $\gamma^\zeta{}_1 = \langle \eta_1, \rho_1, \aleph_1 \rangle$ and $\gamma^\zeta{}_2 = \langle \eta_2, \rho_2, \aleph_2 \rangle$ are the PFNs and $\beth, \beth_1, \beth_2 > 0$ be the real numbers, then we have,

1) $\gamma^\zeta{}_1 \oplus \gamma^\zeta{}_2 = \gamma^\zeta{}_2 \oplus \gamma^\zeta{}_1$
2) $\gamma^\zeta{}_1 \otimes \gamma^\zeta{}_2 = \gamma^\zeta{}_2 \otimes \gamma^\zeta{}_1$
3) $\beth\left(\gamma^\zeta{}_1 \oplus \gamma^\zeta{}_2\right) = \left(\beth\gamma^\zeta{}_1\right) \oplus \left(\beth\gamma^\zeta{}_2\right)$
4) $\left(\gamma^\zeta{}_1 \otimes \gamma^\zeta{}_2\right)^\beth = \gamma^\zeta{}_1^\beth \otimes \gamma^\zeta{}_2^\beth$
5) $(\beth_1 + \beth_2)\gamma^\zeta{}_1 = \left(\beth_1\gamma^\zeta{}_1\right) \oplus \left(\beth_2\gamma^\zeta{}_2\right)$
6) $\gamma^\zeta{}_1^{\beth_1+\beth_2} = \gamma^\zeta{}_1^{\beth_1} \otimes \gamma^\zeta{}_2^{\beth_2}$

If $\eta_{\gamma^\zeta{}_1} = \rho_{\gamma^\zeta{}_1}$ and $\eta_{\gamma^\zeta{}_2} = \rho_{\gamma^\zeta{}_2}$ then from Definition 3 we get, $\eta_{\gamma^\zeta{}_1 \oplus \gamma^\zeta{}_2} \neq \rho_{\gamma^\zeta{}_1 \oplus \gamma^\zeta{}_2}, \eta_{\gamma^\zeta{}_1 \otimes \gamma^\zeta{}_2} \neq \rho_{\gamma^\zeta{}_1 \otimes \gamma^\zeta{}_2}, \eta_{\beth\gamma^\zeta{}_1} \neq \rho_{\beth\gamma^\zeta{}_1}, \eta_{\gamma^\zeta{}_1^\beth} \neq \rho_{\gamma^\zeta{}_1^\beth}$. Thus none of the operations $\gamma^\zeta{}_1 \oplus \gamma^\zeta{}_2, \gamma^\zeta{}_1 \otimes \gamma^\zeta{}_2, \beth\gamma^\zeta{}_1, \gamma^\zeta{}_1^\beth$ found to be neutral or fair indeed. Therefore, our first focus should be on the development of fair operations amongst PFNs.

III. FAIRLY OPERATIONS ON PFNs

In this subsection, we construct and investigate various fairly operations involving PFNs.

Definition 5 [49]: Let $\gamma^\zeta{}_1 = \left\langle \eta_{\gamma^\zeta{}_1}, \rho_{\gamma^\zeta{}_1}, \aleph_{\gamma^\zeta{}_1} \right\rangle$ and $\gamma^\zeta{}_2 = \left\langle \eta_{\gamma^\zeta{}_2}, \rho_{\gamma^\zeta{}_2}, \aleph_{\gamma^\zeta{}_2} \right\rangle$ are two PFNs and $\beth > 0$. Then we define, as shown in the equation at the bottom of the next page.

It can be easily verified that $\gamma^\zeta{}_1 \tilde{\oplus} \gamma^\zeta{}_2, \beth * \gamma^\zeta{}_1$ are the PFNs.

Theorem 1: Consider $\gamma^\zeta{}_1 =< \eta_{\gamma^\zeta{}_1}, \rho_{\gamma^\zeta{}_1}, \aleph_{\gamma^\zeta{}_1} >$ and $\gamma^\zeta{}_2 =< \eta_{\gamma^\zeta{}_2}, \rho_{\gamma^\zeta{}_2}, \aleph_{\gamma^\zeta{}_2} >$ are the PFNs. If $\eta_{\gamma^\zeta{}_1} = \rho_{\gamma^\zeta{}_1}$, $\eta_{\gamma^\zeta{}_2} = \rho_{\gamma^\zeta{}_2}$ and $\aleph_{\gamma^\zeta{}_2} = \aleph_{\gamma^\zeta{}_2}$ then we have

(i) $\eta_{\gamma^\zeta{}_1 \tilde{\oplus} \gamma^\zeta{}_2} = \rho_{\gamma^\zeta{}_1 \tilde{\oplus} \gamma^\zeta{}_2} = \aleph_{\gamma^\zeta{}_1 \tilde{\oplus} \gamma^\zeta{}_2}$
(ii) $\eta_{\beth * \gamma^\zeta{}_1} = \rho_{\beth * \gamma^\zeta{}_1} = \aleph_{\beth * \gamma^\zeta{}_1}$

A. PICTURE FUZZY FAIRLY WEIGHTED AVERAGING (PFFWA) OPERATOR

Definition 6: [49]: Let ${\gamma^\zeta}_h = \langle \eta_h, \rho_h, \aleph_h \rangle$ be the collection of PFNs, and PFFWA: $\mathfrak{G}^n \rightarrow \mathfrak{G}$, be the mapping. If,

$$\begin{aligned} &\mathrm{PFFWA}({\gamma^\zeta}_1, {\gamma^\zeta}_2, \ldots {\gamma^\zeta}_e) \\ &\quad = \left(\mathfrak{W}_1 * {\gamma^\zeta}_1 \tilde{\oplus} \mathfrak{W}_2 * {\gamma^\zeta}_2 \tilde{\oplus} \ldots, \tilde{\oplus} \mathfrak{W}_e * {\gamma^\zeta}_e\right) \end{aligned} \tag{11}$$

then PFFWA is called "picture fuzzy fairly weighted averaging (PFFWA) operator", here $\mathfrak{W}_i$ is the weight vector (WV) of ${\gamma^\zeta}_i$ with $\mathfrak{W}_i > 0$ and $\sum_{i=1}^{e} \mathfrak{W}_i = 1$.

In addition, as proved in the following theorem, we can investigate PFFWA operator.

Theorem 2: [49]: Consider ${\gamma^\zeta}_h = \langle \eta_h, \rho_h, \aleph_h \rangle$ is the family of PFNs, we can evaluate PFFWA operator by

$$\mathrm{PFFWA}({\gamma^\zeta}_1, {\gamma^\zeta}_2, \ldots, {\gamma^\zeta}_e) = \begin{pmatrix} \dfrac{\prod_{i=1}^{e} (\eta_i)^{\mathfrak{W}_i}}{\prod_{i=1}^{e} (\eta_i)^{\mathfrak{W}_i} + \prod_{i=1}^{e} (\rho_i)^{\mathfrak{W}_i} + \prod_{i=1}^{e} (\aleph_i)^{\mathfrak{W}_i}} \times \\ \left(1 - \prod_{i=1}^{e} (1 - \eta_i - \rho_i - \aleph_i)^{\mathfrak{W}_i}\right), \\ \dfrac{\prod_{i=1}^{e} (\rho_i)^{\mathfrak{W}_i}}{\prod_{i=1}^{e} (\eta_i)^{\mathfrak{W}_i} + \prod_{i=1}^{e} (\rho_i)^{\mathfrak{W}_i} + \prod_{i=1}^{e} (\aleph_i)^{\mathfrak{W}_i}} \times \\ \left(1 - \prod_{i=1}^{e} (1 - \eta_i - \rho_i - \aleph_i)^{\mathfrak{W}_i}\right), \\ \dfrac{\prod_{i=1}^{e} (\aleph_i)^{\mathfrak{W}_i}}{\prod_{i=1}^{e} (\eta_i)^{\mathfrak{W}_i} + \prod_{i=1}^{e} (\rho_i)^{\mathfrak{W}_i} + \prod_{i=1}^{e} (\aleph_i)^{\mathfrak{W}_i}} \times \\ \left(1 - \prod_{i=1}^{e} (1 - \eta_i - \rho_i - \aleph_i)^{\mathfrak{W}_i}\right) \end{pmatrix}$$

where $\mathfrak{W}_i$ is the WV of ${\gamma^\zeta}_i$ with $\mathfrak{W}_i > 0$ and $\sum_{i=1}^{e} \mathfrak{W}_i = 1$.

Example 1: Assume ${\gamma^\zeta}_1 = \langle 0.425, 0.255, 0.155 \rangle$, ${\gamma^\zeta}_2 = \langle 0.340, 0.335, 0.120 \rangle$ and ${\gamma^\zeta}_3 = \langle 0.475, 0.145, 0.110 \rangle$ are three PFNs with WV ${\gamma^\zeta} = (0.399, 0.276, 0.325)$, then

$$\mathrm{PFFWA}({\gamma^\zeta}_1, {\gamma^\zeta}_2, {\gamma^\zeta}_3) = \begin{pmatrix} \dfrac{\prod_{i=1}^{3} (\eta_i)^{\mathfrak{W}_i}}{\prod_{i=1}^{3} (\eta_i)^{\mathfrak{W}_i} + \prod_{i=1}^{3} (\rho_i)^{\mathfrak{W}_i} + \prod_{i=1}^{3} (\aleph_i)^{\mathfrak{W}_i}} \times \\ \left(1 - \prod_{i=1}^{3} (1 - \eta_i - \rho_i - \aleph_i)^{\mathfrak{W}_i}\right), \\ \dfrac{\prod_{i=1}^{3} (\rho_i)^{\mathfrak{W}_i}}{\prod_{i=1}^{3} (\eta_i)^{\mathfrak{W}_i} + \prod_{i=1}^{3} (\rho_i)^{\mathfrak{W}_i} + \prod_{i=1}^{3} (\aleph_i)^{\mathfrak{W}_i}} \times \\ \left(1 - \prod_{i=1}^{3} (1 - \eta_i - \rho_i - \aleph_i)^{\mathfrak{W}_i}\right), \\ \dfrac{\prod_{i=1}^{3} (\aleph_i)^{\mathfrak{W}_i}}{\prod_{i=1}^{3} (\eta_i)^{\mathfrak{W}_i} + \prod_{i=1}^{3} (\rho_i)^{\mathfrak{W}_i} + \prod_{i=1}^{3} (\aleph_i)^{\mathfrak{W}_i}} \times \\ \left(1 - \prod_{i=1}^{3} (1 - \eta_i - \rho_i - \aleph_i)^{\mathfrak{W}_i}\right) \end{pmatrix}$$

$$= (0.426140, 0.235385, 0.132880)$$

The presented AO satisfies a number of particular characteristics, which are outlined in the theorems that follow.

Theorem 3: Let ${\gamma^\zeta}_i = \langle \eta_i, \rho_i, \aleph_i \rangle$ be the collection of PFNs and ${\gamma^\zeta}_\diamond = \langle \eta_\diamond, \rho_\diamond, \aleph_\diamond \rangle$ be the PFNs such that, ${\gamma^\zeta}_i = {\gamma^\zeta}_\diamond \forall i$. Then

$$\mathrm{PFFWA}({\gamma^\zeta}_1, {\gamma^\zeta}_2, \ldots, {\gamma^\zeta}_e) = {\gamma^\zeta}_\diamond \tag{12}$$

Theorem 4: Let ${\gamma^\zeta}_i = \langle \eta_i, \rho_i, \aleph_i \rangle$ be the accumulation of PFNs. Then for $\mathrm{PFFWA}({\gamma^\zeta}_1, {\gamma^\zeta}_2, \ldots, {\gamma^\zeta}_e) = \langle \eta_x, \rho_x, \aleph_x \rangle$, we have

$$\min_i \{\eta_i + \rho_i + \aleph_i\} \leq \eta_x + \rho_x + \aleph_x \leq \max_i \{\eta_i + \rho_i + \aleph_i\}$$

$${\gamma^\zeta}_1 \tilde{\oplus} {\gamma^\zeta}_2 = \begin{pmatrix} \left(\dfrac{\eta_{{\gamma^\zeta}_1} \eta_{{\gamma^\zeta}_2}}{\eta_{{\gamma^\zeta}_1} \eta_{{\gamma^\zeta}_2} + \rho_{{\gamma^\zeta}_1} \rho_{{\gamma^\zeta}_2} + \aleph_{{\gamma^\zeta}_1} \aleph_{{\gamma^\zeta}_2}}\right) \times \\ \left(1 - \left(1 - \eta_{{\gamma^\zeta}_1} - \rho_{{\gamma^\zeta}_1} - \aleph_{{\gamma^\zeta}_1}\right)\left(1 - \eta_{{\gamma^\zeta}_2} - \rho_{{\gamma^\zeta}_2} - \aleph_{{\gamma^\zeta}_2}\right)\right), \\ \left(\dfrac{\rho_{{\gamma^\zeta}_1} \rho_{{\gamma^\zeta}_2}}{\eta_{{\gamma^\zeta}_1} \eta_{{\gamma^\zeta}_2} + \rho_{{\gamma^\zeta}_1} \rho_{{\gamma^\zeta}_2} + \aleph_{{\gamma^\zeta}_1} \aleph_{{\gamma^\zeta}_2}}\right) \times \\ \left(1 - \left(1 - \eta_{{\gamma^\zeta}_1} - \rho_{{\gamma^\zeta}_1} - \aleph_{{\gamma^\zeta}_1}\right)\left(1 - \eta_{{\gamma^\zeta}_2} - \rho_{{\gamma^\zeta}_2} - \aleph_{{\gamma^\zeta}_2}\right)\right), \\ \left(\dfrac{\aleph_{{\gamma^\zeta}_1} \aleph_{{\gamma^\zeta}_2}}{\eta_{{\gamma^\zeta}_1} \eta_{{\gamma^\zeta}_2} + \rho_{{\gamma^\zeta}_1} \rho_{{\gamma^\zeta}_2} + \aleph_{{\gamma^\zeta}_1} \aleph_{{\gamma^\zeta}_2}}\right) \times \\ \left(1 - \left(1 - \eta_{{\gamma^\zeta}_1} - \rho_{{\gamma^\zeta}_1} - \aleph_{{\gamma^\zeta}_1}\right)\left(1 - \eta_{{\gamma^\zeta}_2} - \rho_{{\gamma^\zeta}_2} - \aleph_{{\gamma^\zeta}_2}\right)\right) \end{pmatrix}$$

$$\beth * {\gamma^\zeta}_1 = \begin{pmatrix} \left(\dfrac{\eta^{\beth}_{{\gamma^\zeta}_1}}{\eta^{\beth}_{{\gamma^\zeta}_1} + \rho^{\beth}_{{\gamma^\zeta}_1} + \aleph^{\beth}_{{\gamma^\zeta}_1}}\right) \times \left(1 - \left(1 - \eta_{{\gamma^\zeta}_1} - \rho_{{\gamma^\zeta}_1} - \aleph_{{\gamma^\zeta}_1}\right)^{\beth}\right), \\ \left(\dfrac{\rho^{\beth}_{{\gamma^\zeta}_1}}{\eta^{\beth}_{{\gamma^\zeta}_1} + \rho^{\beth}_{{\gamma^\zeta}_1} + \aleph^{\beth}_{{\gamma^\zeta}_1}}\right) \times \left(1 - \left(1 - \eta_{{\gamma^\zeta}_1} - \rho_{{\gamma^\zeta}_1} - \aleph_{{\gamma^\zeta}_1}\right)^{\beth}\right), \\ \left(\dfrac{\aleph^{\beth}_{{\gamma^\zeta}_1}}{\eta^{\beth}_{{\gamma^\zeta}_1} + \rho^{\beth}_{{\gamma^\zeta}_1} + \aleph^{\beth}_{{\gamma^\zeta}_1}}\right) \times \left(1 - \left(1 - \eta_{{\gamma^\zeta}_1} - \rho_{{\gamma^\zeta}_1} - \aleph_{{\gamma^\zeta}_1}\right)^{\beth}\right) \end{pmatrix}$$

Theorem 5: Assume that $\gamma^{\zeta}{}_{i} = \langle \eta_i, \rho_i, \aleph_i \rangle$ and $\gamma^{\zeta}{}_{i*} = \langle \eta_{i*}, \rho_{i*}, \aleph_{i*} \rangle$ are the assemblages of PFNs, and also consider

$$\mathrm{PFFWA}(\gamma^{\zeta}{}_{1}, \gamma^{\zeta}{}_{2}, \ldots \gamma^{\zeta}{}_{e}) = \gamma^{\zeta} = \langle \eta, \rho, \aleph \rangle$$

and

$$\mathrm{PFFWA}(\gamma^{\zeta}{}_{1*}, \gamma^{\zeta}{}_{2*}, \ldots \gamma^{\zeta}{}_{e*}) = \gamma^{\zeta}{}_{*} = \langle \eta_{*}, \rho_{*}, \aleph_{*} \rangle.$$

Then,

$$\eta + \rho + \aleph \leq \eta_{*} + \rho_{*} + \aleph_{*}, \text{ if } \eta_i + \rho_i + \aleph_i \leq \eta_{i*} + \rho_{i*} + \aleph_{i*}$$

IV. ENERGY CONSUMPTION FORECASTING BASED ON MACHINE LEARNING

A. DATASET DESCRIPTION

In this research work, we use smart home dataset that is collected from the kaggle platform.[1] The dataset is comprised of the meter readings of the total electricity consumption, electricity consumption readings of the households' appliances and weather behavior data. The dataset had total 503910 entities and 32 total properties. We divided the total characteristics into two groups; first was weather impact monitoring and second was appliances electricity consumption monitoring can be seen in the Figure 2.

B. DATA PRE-PROCESSING

Data preprocessing in the key activity which involves data preparing and data transforming into suitable data analysis format to facilitate data analysis stage. The objective behind the data preparation is to reduce the data size by cleaning, eliminating outliers, normalizing variables, exploring relationships between variables in order to extract the required set of features [50]. During the data preprocessing, the columns of "KW" were removed, the columns for Kitchen and Furnace joined into new separate column. The NaN row was eliminated from dataset. The invalid entities of cloud cover column were replaced with actual and valid values. There were also duplicate entities in the dataset and these values were excluded and adjusted. The column "House overall" and "use" were combined into "Overall_usage" and the coefficient correlation factor observed which was 0.95. Pandas library used to change the date-time data type from object type to "datetime64[ns]" type. After using pandas library in Python language,[2] the format of data-time was extracted in the format of hour, day, month, and year columns. Therefore, with hour variable, the exact time of observed day was retrieved, for instance, morning time, afternoon time, evening time, or night time.

C. ENERGY DATA ANALYSIS AND VISUALIZATIONS

1) IMPACT OF WEATHER ON ENERGY CONSUMPTION

We used matplotlip library in the smart home dataset setting, we used the variable "overall usage" versus "time" and observed that electricity consumption was at peak in the July, August, and September months. This behavior can be seen in the Figure 3 line. This behavior can also be observed in the second subplot between "temperature and time (months)". This behavior shows that the electricity consumption was low when the temperature was low. Whenever, the temperature started to rise the rise in electricity consumption was also observed in the months of July, August, and September. The comparisons evaluation graph between Weather (temperature) and Furnace can be shown in the Figure 4 below. The pattern in the graph shows there is a clear evidence that temperature has direct influence on the Smart Home Furnace electricity consumption behavior.

2) ENERGY CONSUMPTION BY ROOMS AND APPLIANCES

The behavior of appliances electricity usage inside different rooms for every single day can be seen in the Figure 5 below and can be observed that Furnace and Barn consumed higher number of electricity units. From the Figure 6 below, the electricity usage behavior for appliances and rooms can be observed. It can be seen that Furnace, barn, and refrigerator consumed higher number of electricity units.

3) ENERGY CONSUMPTION BY ROOMS

The Figure 7 below explains the appliances electricity usage inside rooms of Smart Home. It shows that the office room in home consumed the highest electricity units and the Kitchen consumed least number of units likened to other Smart Home rooms.

4) ENERGY CONSUMPTION BY APPLIANCES

It can be seen the monthly electricity usage behavior of Smart Home appliances from the Figure 8 below. It can be observed from the graph that Furnace consumed comparatively more electricity than any other appliance. The other appliances which showed high consumption of electricity after Furnace are Refrigerator and Dishwasher. From the Figure 9, it can also observed that microwave, well, and garage consumed less electricity units. It was observed that Furnace consumed highest percent of electricity and was responsible about 63.49 % of total Smart Home's appliances electricity and Refrigerator ranked second accounting 17.10% of electricity consumption. The other appliances such as microwave, dishwasher, garage door, well etc of Smart Home jointly consumed 19.4% electricity consumption.

The appliances showed identical consumption behavior of in all other months except, the highest number of electricity units consumed in the month of August and can be seen in the Figure 10.

It was observed and can be seen in the Figure 11 that Home Office room consumed maximum electricity units about 36% of total Smart Home's electricity, Barn was on second number, consumed about 26%. Living Room and Wine Cellar consumed 34% of electricity jointly. Kitchen was the room which consumed least number of electricity units about 4.3%.

[1] https://www.kaggle.com/code/malekzadeh/smart-home-data-processing-weather-vs-energy/data

[2] https://github.com/pandas-dev/pandas

Sr. No.	Features Categories	Features-Before Pre-processing
1	Total Power Consumption	Overall, Home
		Use
2	Home Appliances	Dishwasher
		Furnace 1
		Furnace 2
		Home Office
		Fridge
		Wine cellar
		Garage door
		Kitchen 12
		Kitchen 14
		Kitchen 38
		Barn
		Well
		Microwave
		Living Room
3	Weather Information	Temperature
		Humidity
		Visibility
		Icon
		Summary
		Apparent Temperature
		Pressure
		Wind Speed
		Cloud Cover
		Wind Bearing
		Dew Point
		Probability of precipitation
		Precipitation Intensity

FIGURE 2. Dataset description.

5) ENERGY CONSUMPTION BY DAYS

Total electricity consumption (kilowatts) of every single day in the whole week can be seen in the Figure 12 below. It is evident from the graph that users consumed maximum electricity on the day of Monday during the whole week and Wednesday bar chart showed the lowest electricity consumption during the week. The electricity consumption was measured in KW. It was observed that maximum electricity consumed during the night time which was 140,000 kW for Smart Home. The following 120,000 kW and 90,000 kW reading were observed during Morning and Evening time, respectively and the afternoon time showed the lowest consumption approximately, which is 70,000 kW.

6) CORRELATION OF ENERGY CONSUMPTION DATA USING HEATMAP

The correlation between energy appliances can be seen in the Figure 14. The graph shows that there is no clear evidence of correlation among various appliances.

The weather information can be seen in the form of heatmaps in the Figure 15:

Temperature is correlated to dewpoint and apparentTemperature. CloudCover is correlated to precipIntensity, visibility, apparentTemperature and humidity. Humidity is associated to dewpoint, cloudCover, and windSpeed. Visibility is associated to precipIntensity, cloudCover, and windSpeed. PrecipIntensity is correlated to cloudCover and

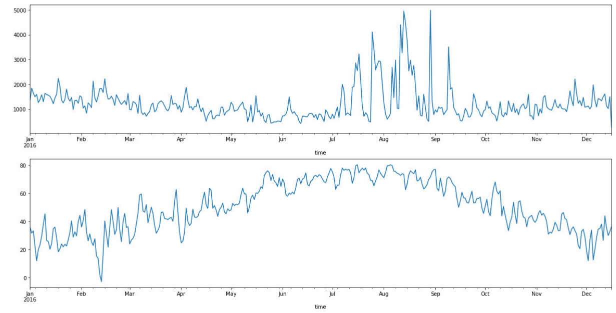

FIGURE 3. Temperature and electricity consumption.

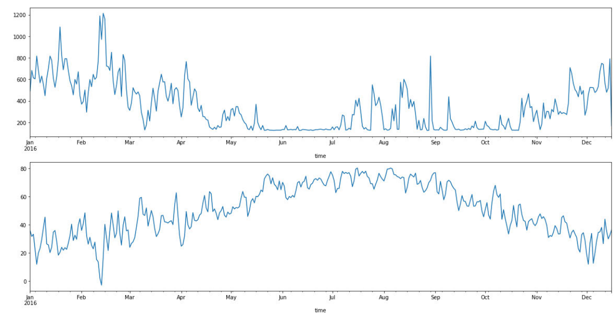

FIGURE 4. Impact of furnace and outside temperature on electricity consumption.

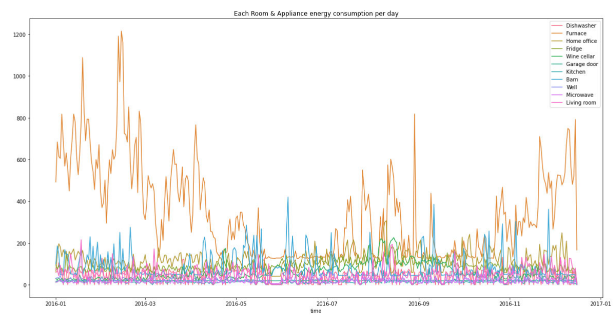

FIGURE 5. Per day electricity consumption by appliances and rooms.

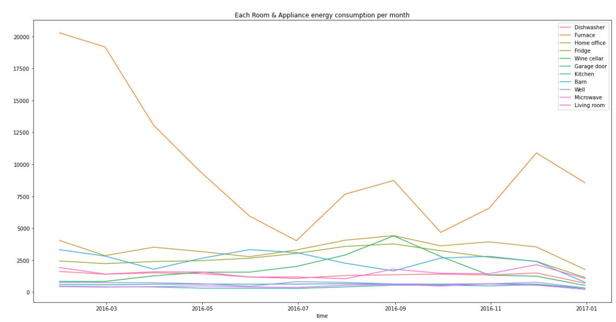

FIGURE 6. Per month electricity consumption by appliances and rooms.

visibility. DewPoint is correlated to humidity, temperature, and apparentTemperature.

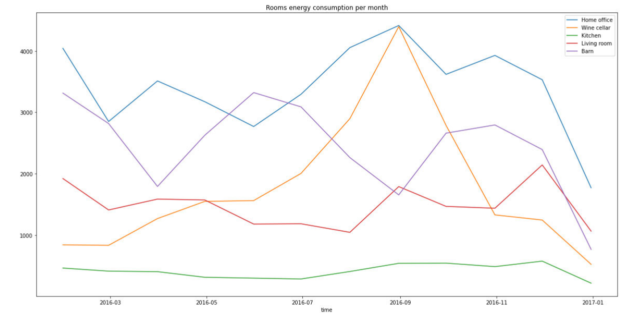

FIGURE 7. Per month electricity consumption by rooms.

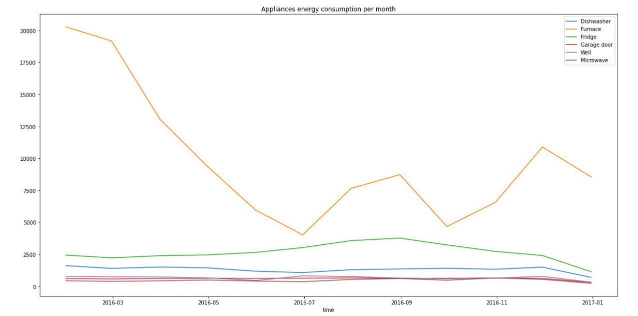

FIGURE 8. Per month electricity consumption by appliances.

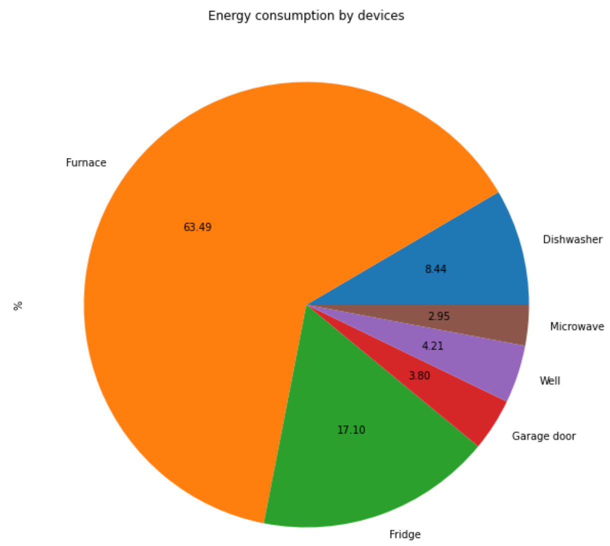

FIGURE 9. % Electricity consumption by appliances (in percentage).

From the correlation heatmaps in the Figure 16 of appliances with weather data, it was observed that appliances behavior was influenced by weather information and related factors. Wine cellar consumption was influenced and associated to dew point, temperature, and apparent temperature. Furnace consumption was influenced and associated to dew point, temperature, apparent temperature, and wind speed.

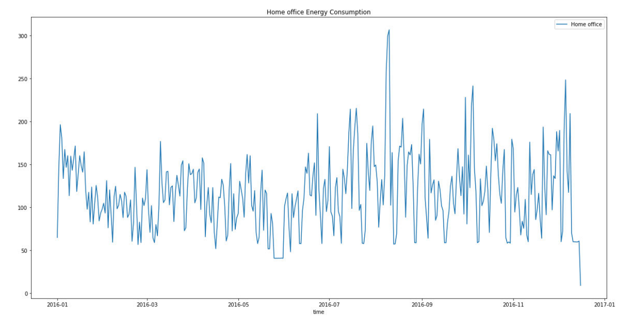

FIGURE 10. Home office room electricity consumption (in percentage).

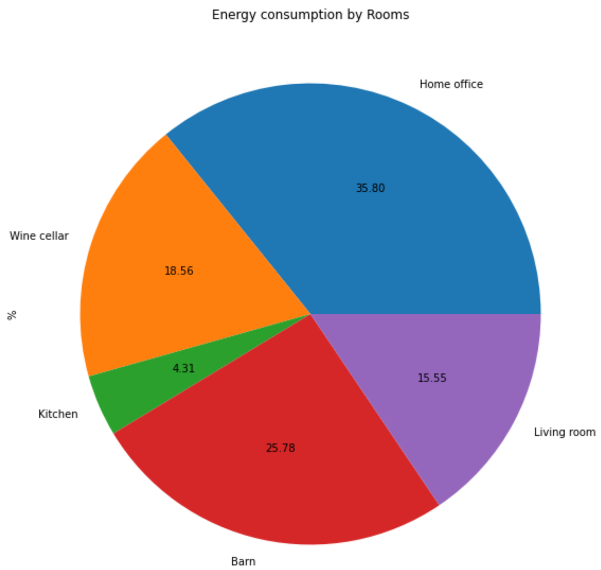

FIGURE 11. % Total electricity consumption by rooms (in percentage).

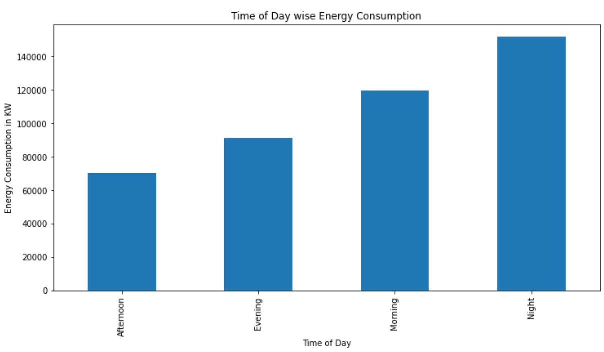

FIGURE 12. Per time total electricity consumption (kW) in a day.

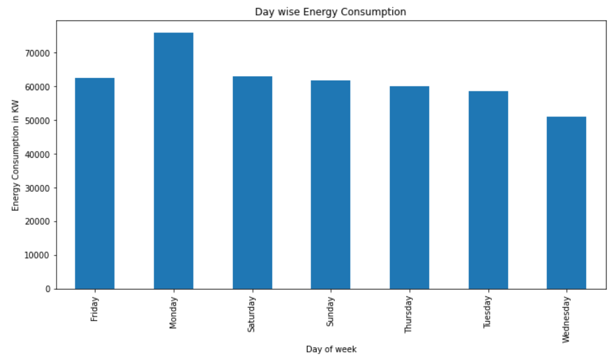

FIGURE 13. Per day total electricity consumption (kW) in a week.

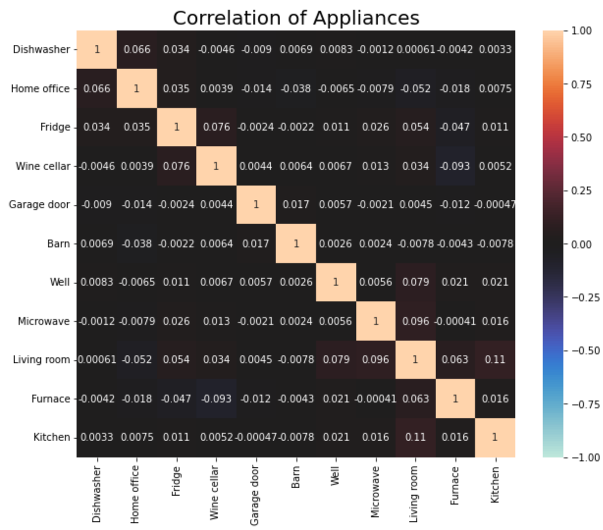

FIGURE 14. Correlation between electrical appliances.

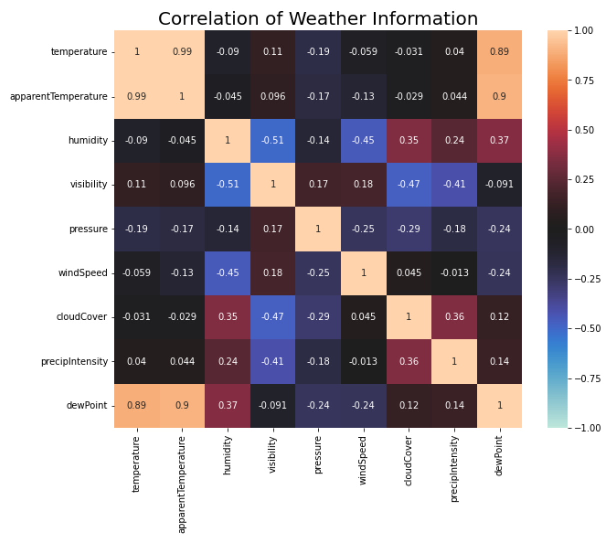

FIGURE 15. Correlation of weather information.

Fridge consumption was influenced and associated to dew point, temperature, and apparent temperature.

7) FEATURE TRANSFORMATION

Feature transformation helps to deal with the selection of feature values and feature evaluation using machine learning models. Some machine learning models have showed better prediction accuracy in terms of feature selection with less training time and well convergence rate [51].

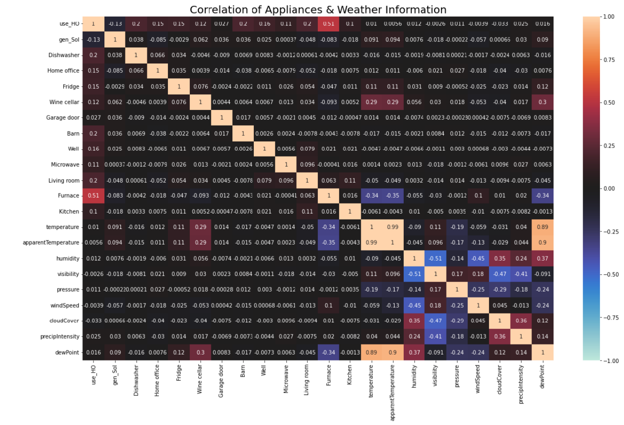

FIGURE 16. **Correlation of appliances and weather information.**

a: STANDARD SCALER

We used sklearn.preprocessing library and the StandardScaler function for the scaling of raw data. In this process, we removed the variable "Overall Usage" from the dataset to better examine the scaling of dataset.

b: PRINCIPAL COMPONENT ANALYSIS

We employed Principal Component Analysis (PCA) using sklearn.decomposition function to minimize the dimensionality issue. We observed that after implementing the Principal Component Analysis (PCA), the dataset condensed the columns length from 29 to 22 columns length with the variance rate of 95%.

8) TRAINING/ TESTING DATA SPLIT

For this project, we used dataset of 350 days. We split up the dataset into 348 days for training module and 2 days data for testing module to observe the prediction accuracy of selected machine learning models.

a: MODEL IMPLEMENTATION

This section is divided into two subsections; training section and testing section using smart home energy consumption dataset.

9) TRAINING THE ML MODELS

a: SUPPORT VECTOR REGRESSION MODEL (SVR)

The environment for support vector regression was initiated using "sklearn.svm" command and variable "svr". After that, the dataset was trained.

b: LINEAR REGRESSION MODEL

The environment for support vector regression was also initiated using "sklearn.svm" command and variable "lm". After creating this environment, the dataset was trained using the package "sklearn.model_selection package".

c: RANDOM FOREST REGRESSOR MODEL

The environment and variable for random forest regressor was also initiated using "sklearn.ensemble" package command and variable "Rfr". After creating this ML environment, the dataset was trained using the package "sklearn.model_selection package".

d: DECISION TREE REGRESSOR MODEL

The environment and variable for decision tree regressor was also initiated using "sklearn.tree" package command and variable "dtreg". After creating this ML environment, the dataset was trained using the package "sklearn.model_selection package".

e: K NEAREST NEIGHBORS REGRESSOR MODEL

The environment and variable for k-nearest neighbors regressor was also initiated using "sklearn.neighbors" package command and variable "knn". After creating this ML environment, the dataset was trained using the package "sklearn.model_selection package".

f: ARTIFICIAL NEURAL NETWORKS

The environment for neural network model was initiated using tensorflow and the function "tensorflow.keras.models" package command and dense function "tensorflow.keras.layers" was also operated using three activation layers connected with four nodes showing output having single node with it.

10) TESTING THE REGRESSION MODELS

a: SUPPORT VECTOR REGRESSION MODEL

After training of dataset using Support Vector Regression model, the testing was applied using variable "svr" to examine the prediction accuracy using two days data. The predictions were observed and recorded under the variable "preds svr.".

b: LINEAR REGRESSION MODEL

After training of dataset using Linear Regression model, the testing was applied using variable "lm" to examine the prediction accuracy using two days data. The predictions were observed and recorded under the variable "preds_lr.".

c: RANDOM FOREST REGRESSOR MODEL

After training of dataset using Random Forest Regressor model, the testing was applied using variable "rfr" to examine the prediction accuracy using two days data. The predictions were observed and recorded under the variable "preds rfr.".

d: DECISION TREE REGRESSOR MODEL

After training of dataset using Decision Tree Regression model, the testing was applied using variable "dtreg" to examine the prediction accuracy using two days data. The

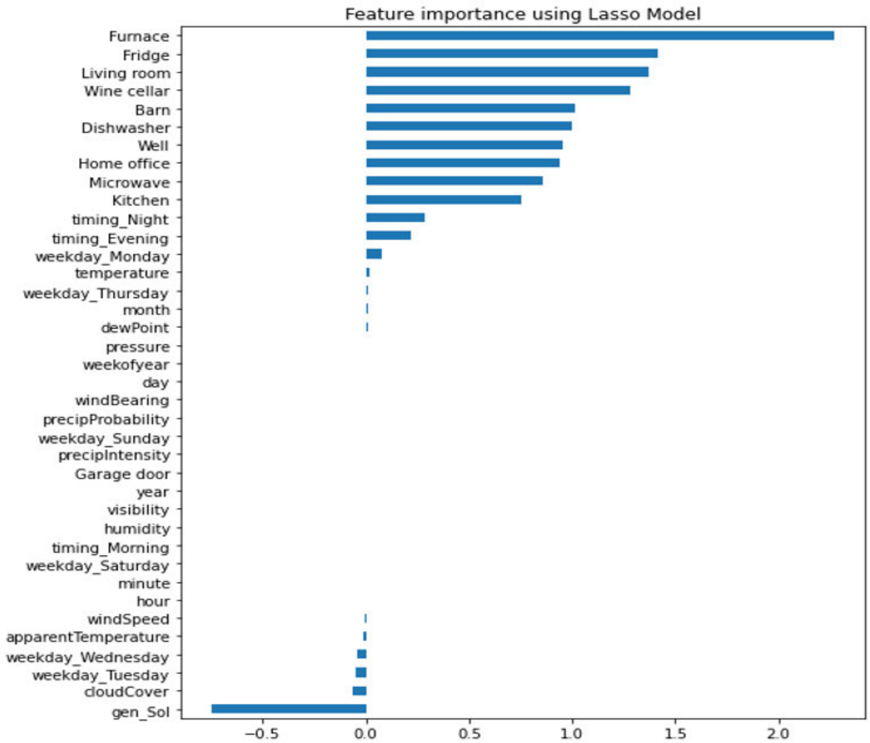

FIGURE 17. Feature importance score using lasso model.

predictions were observed and recorded under the variable "preds_dt.".

e: K NEAREST NEIGHBORS REGRESSOR MODEL

After training of dataset using k Nearest Neighbors Regressor model, the testing was applied using variable "knn" to examine the prediction accuracy using two days data. The predictions were observed and recorded under the variable "preds_knn.".

f: ARTIFICIAL NEURAL NETWORKS

After training of dataset using k Nearest Neighbors Regressor model, the testing was applied using variable "model" to examine the prediction accuracy using two days data. The predictions were observed and recorded under the variable "preds_nn.".

11) FEATURE IMPORTANCE

Lasso Regression: In this subsection, Lasso Regression model is employed and examined to understand and observe the behaviour of features which had high impact during calculating prediction accuracy. The score value of lasso regression was recorded and showed that the impact of weather information (dew point, temperature, cloud cover etc.) is important for predicting the behaviour of electricity consumption.

It can be observed from the lasso model, the scores values of various features such as weather, appliances, timing, rooms had high score values and can be seen in the Figure 17. Among all features, furnace showed highest score value.

V. EXPERIMENTAL RESULTS

The dataset of total 348 days is used to train all the Machine Learning models. The models are, then, tested on 2 days data to evaluate their performances. This section describes the evaluation outcome of all the models.

A. SUPPORT VECTOR REGRESSION (SVR)

The Support Vector Regression (SVR), at first,is trained on the dataset of 348 days. Rest of the data is used for the energy consumption prediction for the next two days. The regression plot of SVR is demonstrated in Figure 19. The evaluation matrix shows that the errors values of Mean Absolute Error (MAE) is 0.13, Mean Squared Error is 0.37 and Root Mean Error is 0.19. The correlation is also observed between SVR's prediction and the actual energy consumption.

The energy consumption predicted by the support vector regression model and the actual energy consumption using the smart home's data are shown in the graph demonstrated in Figure 20. This clearly shows that the model accurately forecasts the results with better predictions accuracy.

B. LINEAR REGRESSION (LR)

The same training and testing process as it was previously applied on SVM is again applied on the Linear Regression Model i.e., 348 days data for training and 2 days data for test-

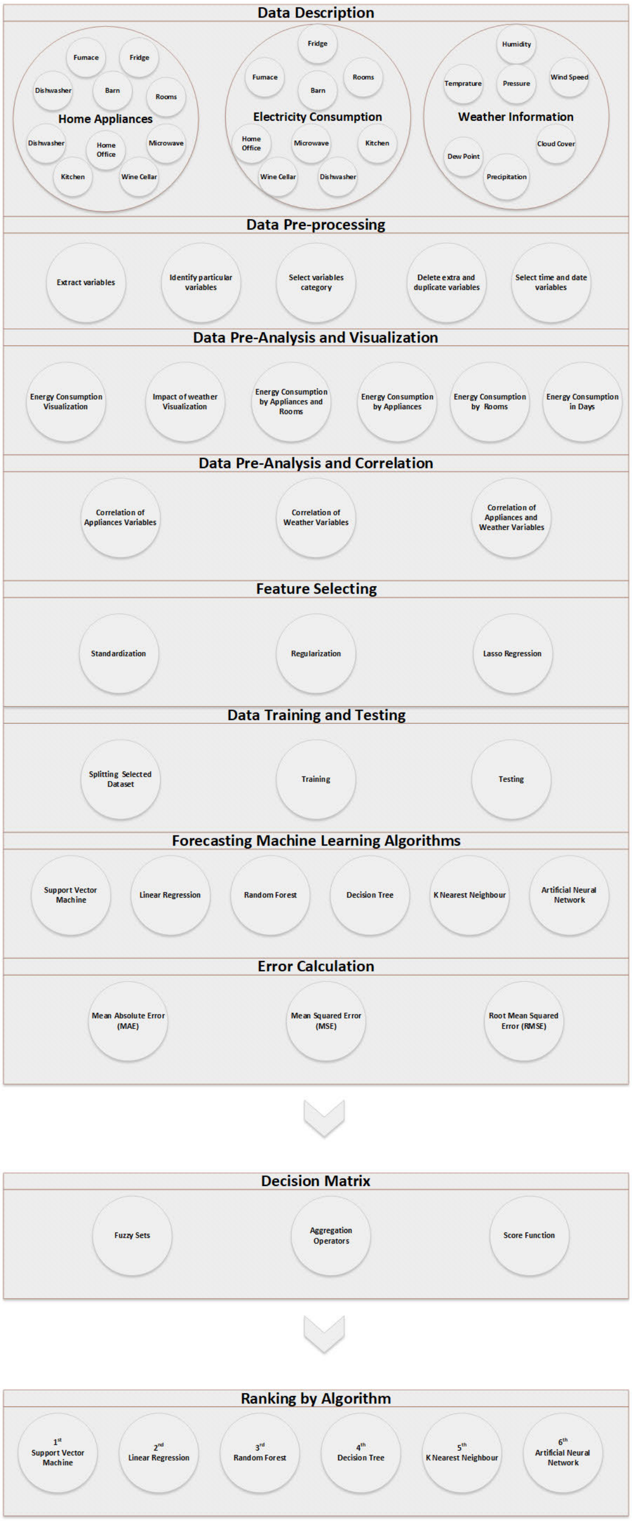

FIGURE 18. Overall flowchart (Step-by-Step process to develop decision matrix).

ing. The regression plot of LR is demonstrated in Figure 21. The evaluation matrix shows that the Mean Absolute Error (MAE) is 0.42, Mean Square Error (RME) is 0.28, and Root Mean Error (RME) is 0.53. It is also observed that the prediction performance of Linear Regression model was relatively low. This prediction performance is shown in the graph that is presented in Figure 22.

It is evident from the graph (shown in Figure 22) that comparing the actual energy consumption to that predicted by the linear regression model, the model overpredicts or fails to understand the values.

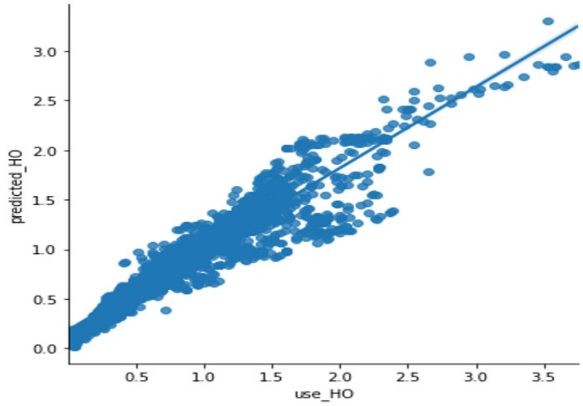

FIGURE 19. Regression plot of support vector regression model.

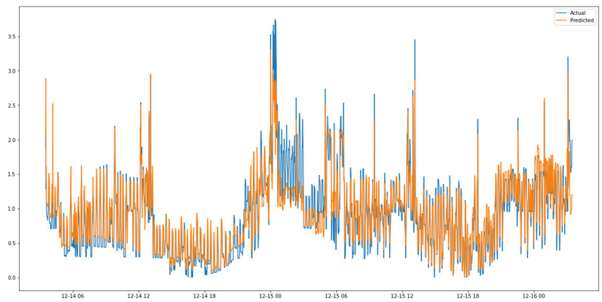

FIGURE 20. Line chart representing the actual and support vector regression model's predicted energy consumption.

C. RANDOM FOREST REGRESSOR (RFR)

The evaluation of RFR shows the following error rates; Mean Absolute Error (MAE) is 0.17, Mean Square Error (MSE) is 0.07, and Root Mean Error (RME) is 0.26. It was also observed that the prediction performance of Random Forest Regressor model was appeared relatively high. The regression plot of RFR is displayed in Figure 23. The output of the prediction on 2-days data is demonstrated in the Figure 24.

Random Forest Regressor model predicted energy consumption effectively, but it was also observed that Random Forest Regressor often overpredicted the consumption pattern which can be shown in the figure below.

D. DECISION TREE REGRESSOR (DTR)

DTR shows the following error rates; Mean Absolute Error (MAE)=0.25, Mean Square Error (MSE)=0.16, and Root

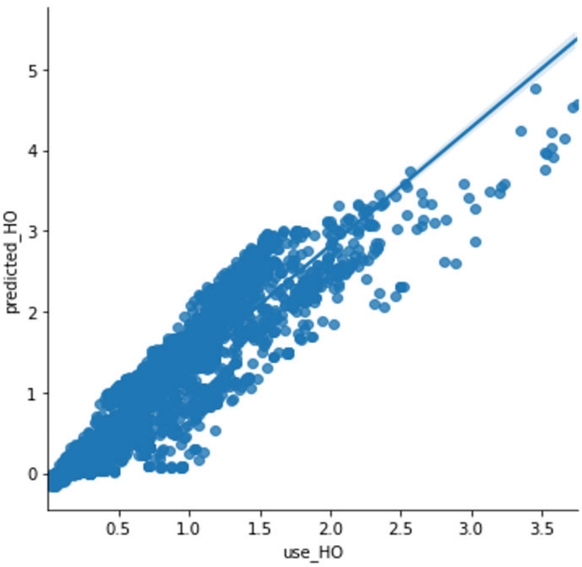

FIGURE 21. Regression plot of linear regression model.

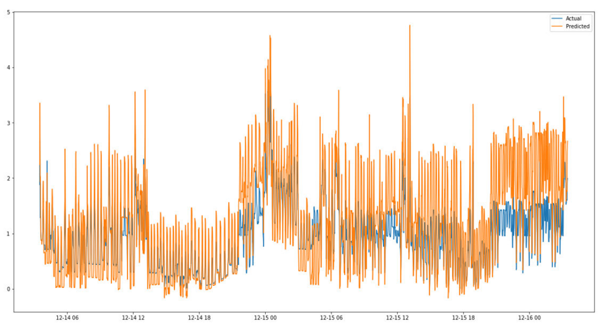

FIGURE 22. Prediction of electricity consumption by actual and linear regression model.

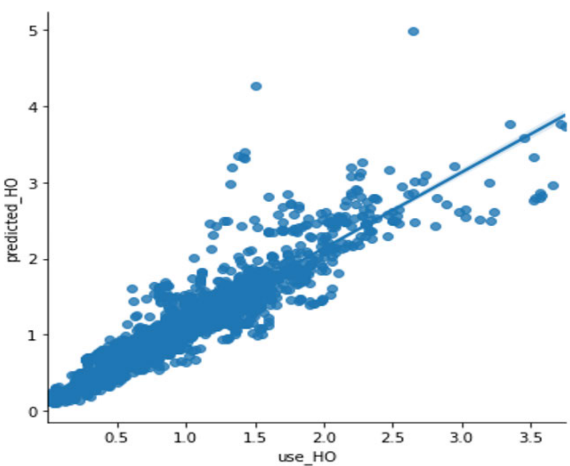

FIGURE 23. Regression plot of random forest regressor model.

Mean Error (RME)=0.39. Regression plot of DTR is demonstrated in Figure 25. The prediction performance of DTR

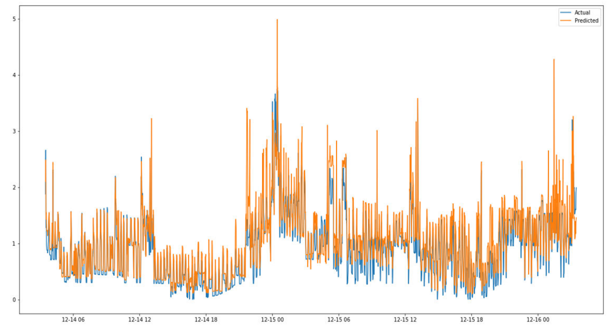

FIGURE 24. Prediction of electricity consumption by actual and random forest regressor model.

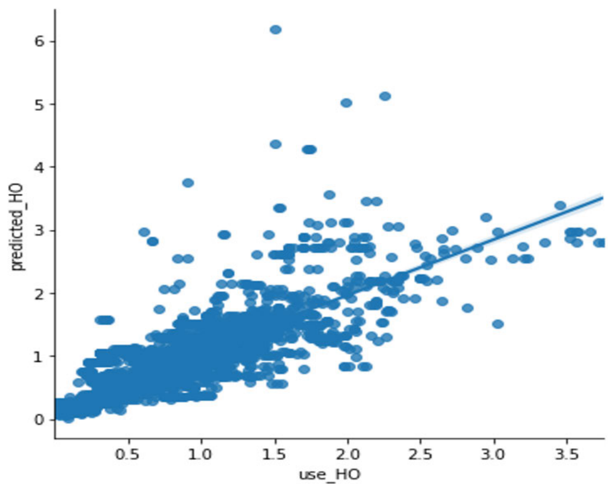

FIGURE 25. Regression plot of decision tree regressor model.

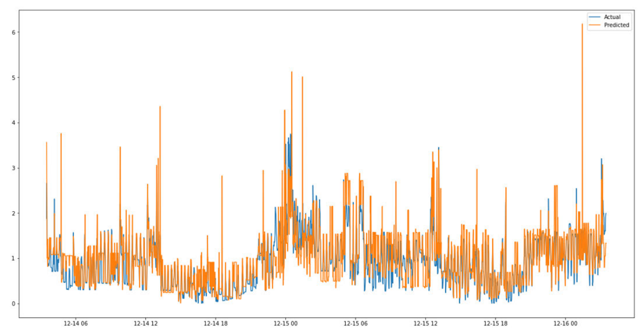

FIGURE 26. Prediction of electricity consumption by actual and decision tree regressor model.

is demonstrated in Figure 25 which clearly shows lack of accuracy in certain patterns of energy consumption over the 2-days timescale. This also indicates that there is inadequate correlation between the actual energy used in the smart home and the expected energy consumption numbers from the decision tree regressor model.

E. k NEIGHBORS REGRESSOR (KNR)

The following error rates were observed in the KNR model; Mean Absolute Error (MAE) = 0.15, Mean Square Error

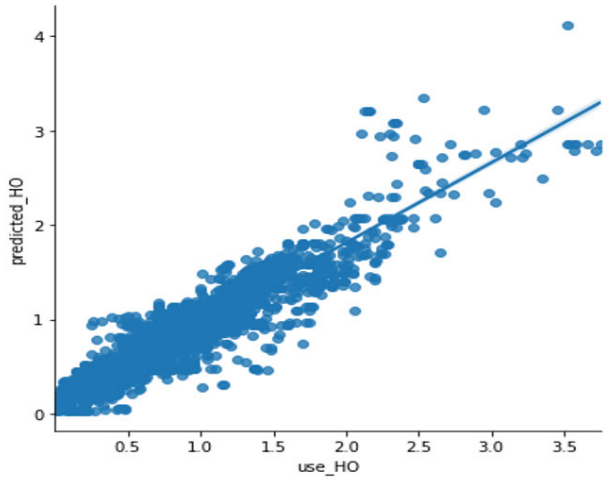

FIGURE 27. Regression plot of k nearest neighbors regressor model.

(MSE) = 0.04, and Root Mean Error (RME) = 0.21. It was also observed that the prediction performance of k-Neighbors Regressor model was appeared relatively high. This prediction performance can be shown in the Picture 27. The significant correlation was observed between k Neighbors Regressor's prediction and the actual outcome. This is demonstrated in the Figure 28.

F. NEURAL NETWORKS (NNs)

The performance evaluation of NNs shows the following error rates; Mean Absolute Error (MAE) = 0.11, Mean Square Error (MSE) = 0.02, and Root Mean Error (RME) = 0.14. It is also observed that the prediction performance of Neural Networks model is remarkably high. The regresson plot of NNs is demonstrated in Figure 31.

The graph that is demonstrated in Figure 32, compares the performance of two days energy consumption data and to the energy consumption predicted by the neural network model. The amount of energy that consumed appears to be well predicted by the model.

G. MODEL PERFORMANCE COMPARISON

According to errors measures, Support Vector Regressor, Neural Networks, and k Nearest Neighbors Regressor are the top models in terms of low error rates of Mean Absolute Error (MAE), Root Mean Error (RMSE), and Mean Square Error (MSE). The SVR and neural network models outperformed other models in forecasting the smart house's energy consumption with error values of 0.19 kW and 0.14 kW, respectively (minute frequency).

The model's performance as determined by the evaluation metrics is summarised in the Figure 29. In order to investigate the error rates of all examined models, the actual and forecast energy consumption data is re-sampled to investigate and evaluate the models performance from minute prediction rate to calendar day prediction rate. With a Root Mean Error (RMSE) 40.15, the support Vector Regressor model performed well after re-sampling the energy consumption data. K-nearest neighbours and Neural network have 48.99 and 58.97 RMSE.

Figure 30 shares information of errors in the form of evaluation metrics on the machine learning model's performance after re-sampling the data.

TABLE 1. Linguistic terms for DMs.

Linguistic terms	PFNs
Very appropriate	0.75, 0.10, 0.05
Appropriate	0.60, 0.15, 0.10
Medium appropriate	0.50, 0.20, 0.15
Un-appropriate	0.25, 0.35, 0.25
Very un-appropriate	0.10, 0.40, 0.45

VI. PICTURE FUZZY AGGREGATION APPROACH

We analyse an MCDM conundrum by comparing each of the n distinct solutions to a set of m distinct qualities. In this circumstance, it is crucial to supply a team of p experts whose ratings must be more than zero, but whose aggregate is one.

As you probably recalled, the A_j $(j = 1, 2, \ldots, n)$ alternative must be provided by a D_k $(k = 1, 2, \ldots, p)$ team of experts. The attributes C_i $(i = 1, 2, \ldots, m)$ were likewise chosen by experts after deliberation, hence the evaluation result is expressed in terms of PFNs, $\gamma^{\zeta p}_{ji} = \left\langle \eta^p_{ji}, \rho^p_{ji}, \aleph^p_{ji} \right\rangle$ under the conditions, $0 \leq \eta^p_{ji}, \rho^p_{ji}, \aleph^p_{ji} \leq 1$ and $0 \leq \eta^p_{ji} + \rho^p_{ji} + \aleph^p_{ji} \leq 1$. Moreover, take $\mathfrak{R}^{\gamma}{}_t$ is the WV for the attributes C_i conforming to the limitations, $\mathfrak{R}^{\gamma}{}_t \geq 0$ and $\sum_{t=1}^{m} \mathfrak{R}^{\gamma}{}_t = 1$. The recommended operator is used to construct an MCDM for the PF data, which includes the following steps:

Step 1: Determine the DM ratings represented as PFNs using "linguistic terms" (LTs). LTs are given in Table 1. Assume $\Upsilon_k = \left\langle \eta_k, \rho_k, \aleph_k \right\rangle$ is the PFN for k-th DM. Consequently, the amplitude of the k-th DM, ζ_k, can be calculated as obeys::

$$\zeta_k = \frac{\Upsilon_k}{\sum_{k=1}^{p} \Upsilon_k}, \quad k = 1, 2, 3, \ldots, p \tag{13}$$

where $\Upsilon_k = \eta_k + (1 - \eta_k - \rho_k - \aleph_k) \left(\frac{\rho_k}{\eta_k + \rho_k + \aleph_k} \right) \left(\frac{\aleph_k}{\eta_k + \rho_k + \aleph_k} \right)$ and Clearly $\sum_{k=1}^{p} \zeta_k = 1$

Step 2: Evaluate the decision matrix $\mathscr{E}^{\mathcal{G}}{}_{(p)} = (\mathfrak{Y}^{(p)}_{ji})_{n \times m}$ using the PFNs by the DMs.

Step 3: Establish an integrated PF assessment matrix. It is crucial to note that, while generating the aggregated PF decision framework utilising a group decision-making approach, all separate perspectives must be summed and included to establish a collective viewpoint. The proposed AO will provide the accompanying to this end:

Let $H = \left(H_{ji} \right)_{n \times m}$ be the aggregated PF decision matrix, where

$$H_{ji} = PFFWA \left(\mathfrak{Y}^{(1)}_{ji}, \mathfrak{Y}^{(2)}_{ji}, \ldots, \mathfrak{Y}^{(p)}_{ji} \right)$$

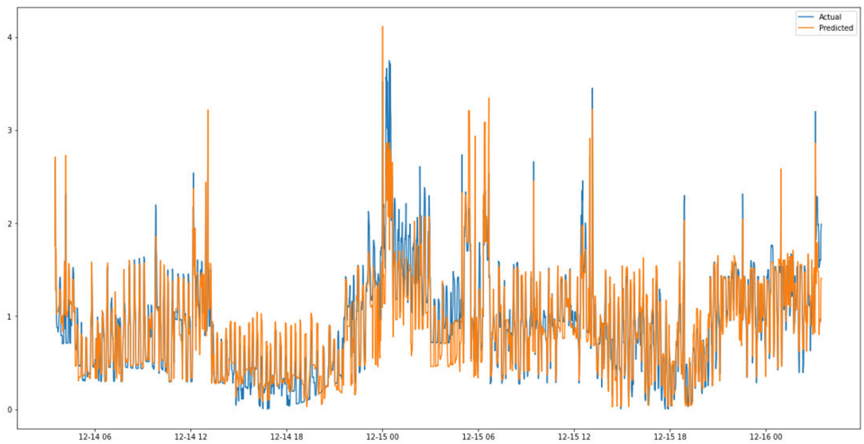

FIGURE 28. Line chart representing the actual and k nearest neighbors regressor model's predicted energy consumption.

Model	Mean Absolute Error (MAE)	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)
Support Vector Regression	0.13	0.37	0.19
Linear Regression	0.42	0.28	0.53
Random Forest Regressor	0.17	0.07	0.26
Decision Tree Regressor	0.25	0.16	0.39
kNeighbors Regressor	0.15	0.04	0.21
Neural Networks	0.11	0.02	0.14

FIGURE 29. Performance evaluation.

Model	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)
Support Vector Regression	30.96	40.15
Linear Regression	301.38	335.73
Random Forest Regressor	126.61	150.66
Decision Tree Regressor	85.50	104.48
kNeighbors Regressor	37.89	48.99
Neural Networks	45.54	58.97

FIGURE 30. After resampling performance evaluation.

For convenience, we take H_{ji} as $H_{ji} = \left\langle \eta_{ji}, \rho_{ji}, \aleph_{ji} \right\rangle$

Step 4: Using the accompanying formula, normalise the PFNs if necessary by transforming any price type features ($\aleph_c$) to benefit kind attributes ($\aleph_b$).

$$(\aleph_{ji}^{N})_{n\times m} = \begin{cases} (H_{ji})^c; & i \in \aleph_c \\ H_{ji}; & i \in \aleph_b. \end{cases} \tag{14}$$

where $(H_{ji})^c$ show the compliment of (H_{ji}). The normalised decision matrix will be $\Gamma_N = \left(\aleph_{ji}^{N}\right)_{n\times m} = \left(\breve{\eta}_{ji}, \breve{\rho}_{ji}, \breve{\aleph}_{ji}\right)_{n\times m}$.

Step 5: Construct the score matrix by include the SF of the PFNs as $\Psi = \left(\breve{\eta}^{\daleth}\left(\aleph_{ji}^{N}\right)\right)_{n\times m}$.

TABLE 2. Criterion for regression models and forecasting.

	Criterion
C_1	Weather information
C_2	Appliance behaviour
C_3	Energy consumption
C_4	Performance evaluation

Step 6: The weighted total of the scores of all options A_j is given by the scoring matrix notion Ψ.

$$¥(A_j) = \sum_{i=1}^{m} \mathfrak{R}^{\gamma}{}_i\, \breve{\eta}^{\daleth}\left(\aleph_{ji}^{N}\right), \quad (j = 1, 2, \ldots, n).$$

where, $\mathfrak{R}^{\gamma}{}_1, \mathfrak{R}^{\gamma}{}_2, \ldots \mathfrak{R}^{\gamma}{}_m$ be the WV of the given criterion.

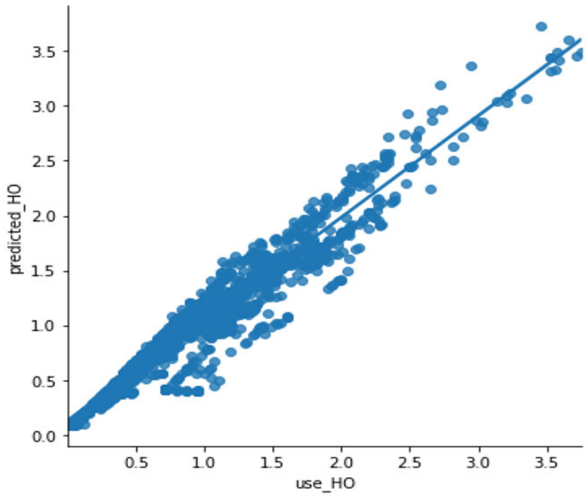

FIGURE 31. Regression plot of neural networks model.

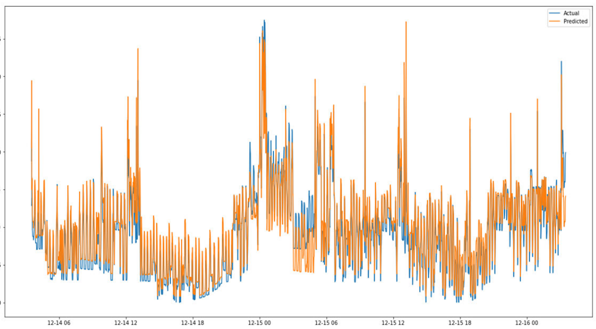

FIGURE 32. Line chart representing the actual and neural networks model's predicted energy consumption.

Assume that the weights are indeterminate and that *prod* represents a collection of them. To compute these indeterminate weights, we apply the preceding mathematical framework,

$$Max \;\; g = \sum_{i=1}^{m} ¥(A_j)$$

under the constraints $\sum_{i=1}^{m} \mathfrak{R}^{\gamma}{}_i = 1$. Using this approach, our normalised WV can be calculated. To calculate the weights of criterion within the constraints of this circumstance, we adopt a linear programming paradigm in this instance.

Step 7: Construct the consolidated weighted PF decision matrix by using a normalised decision matrix Γ_N and the WV $\mathfrak{R}^{\gamma}$. We utilised the following suggested AOs.

$$PFFWA(\aleph^N_{j1}, \aleph^N_{j2}, \ldots, \aleph^N_{jm})$$

$$= \left(\begin{array}{l} \dfrac{\prod_{j=1}^{m} \left(\breve{\eta}_{j\eta_{(i)}}\right)^{\mathfrak{R}^{\gamma}{}_i}}{\prod_{j=1}^{m}\left(\breve{\eta}_{j\eta_{(i)}}\right)^{\mathfrak{R}^{\gamma}{}_i} + \prod_{j=1}^{m}\left(\breve{\rho}_{j\eta_{(i)}}\right)^{\mathfrak{R}^{\gamma}{}_i} + \prod_{j=1}^{m}\left(\breve{\aleph}_{j\eta_{(i)}}\right)^{\mathfrak{R}^{\gamma}{}_i}} \times \\ \left(1 - \prod_{j=1}^{m}\left(1 - \breve{\eta}_{j\eta_{(i)}} - \breve{\rho}_{j\eta_{(i)}} - \breve{\aleph}_{j\eta_{(i)}}\right)^{\mathfrak{R}^{\gamma}{}_i}\right), \\ \dfrac{\prod_{j=1}^{m} \left(\breve{\rho}_{j\eta_{(i)}}\right)^{\mathfrak{R}^{\gamma}{}_i}}{\prod_{j=1}^{m}\left(\breve{\eta}_{j\eta_{(i)}}\right)^{\mathfrak{R}^{\gamma}{}_i} + \prod_{j=1}^{m}\left(\breve{\rho}_{j\eta_{(i)}}\right)^{\mathfrak{R}^{\gamma}{}_i} + \prod_{j=1}^{m}\left(\breve{\aleph}_{j\eta_{(i)}}\right)^{\mathfrak{R}^{\gamma}{}_i}} \times \\ \left(1 - \prod_{j=1}^{m}\left(1 - \breve{\eta}_{j\eta_{(i)}} - \breve{\rho}_{j\eta_{(i)}} - \breve{\aleph}_{j\eta_{(i)}}\right)^{\mathfrak{R}^{\gamma}{}_i}\right), \\ \dfrac{\prod_{j=1}^{m} \left(\breve{\aleph}_{j\eta_{(i)}}\right)^{\mathfrak{R}^{\gamma}{}_i}}{\prod_{j=1}^{m}\left(\breve{\eta}_{j\eta_{(i)}}\right)^{\mathfrak{R}^{\gamma}{}_i} + \prod_{j=1}^{m}\left(\breve{\rho}_{j\eta_{(i)}}\right)^{\mathfrak{R}^{\gamma}{}_i} + \prod_{j=1}^{m}\left(\breve{\aleph}_{j\eta_{(i)}}\right)^{\mathfrak{R}^{\gamma}{}_i}} \times \\ \left(1 - \prod_{j=1}^{m}\left(1 - \breve{\eta}_{j\eta_{(i)}} - \breve{\rho}_{j\eta_{(i)}} - \breve{\aleph}_{j\eta_{(i)}}\right)^{\mathfrak{R}^{\gamma}{}_i}\right) \end{array} \right)$$

Step 8: Using SF, determine the score value of the overall weighted aggregated result. Evaluate each alternative depending on the SF, and then choose the alternate with the greatest SF(s).

A. DECISION-MAKING PROCESS

The specific statement about the regression models and forecasting is described as follows:

If we consider there are six models, namely A_1 = support vector regression model, A_2 = artificial neural networks, A_3 = decision tree regressor model, A_4 = random forest regression model, A_5 = linear regression model and A_6 = k nearest neighbors regressor model. Three experts/decision-makers will be selected to analyze the regression models based on the indications listed in Table 2.

TABLE 3. Linguistic terms for DMs.

DM	Linguistic terms
D_1	Medium appropriate
D_2	Appropriate
D_3	Very appropriate

Step 1: LTs for each DM (doctor) given in Table 3. By the LTs find the DMs weights by the Equation 13, Then the DMs weight are $\zeta_1 = 0.28$, $\zeta_2 = 0.33$ and $\zeta_3 = 0.39$.

Step 2: Obtain the decision matrix $\mathscr{E}^{\mathcal{G}}{}_{(p)} = (\mathfrak{Y}^{(p)}_{ji})_{n\times m}$ in the format of PFNs from DMs. The judgement values, given by three DMs, are given in Table 3, Table 4 and Table 5.

Step 3: To develop the consolidated PF decision matrix, all single views must be summed and combined to establish a collective viewpoint.

$H = \left(H_{ji}\right)_{5\times 4}$ be the consolidated PF decision matrix, where

$$\begin{aligned} H_{ji} &= PFFWA\left(\mathfrak{Y}^{(1)}_{ji}, \mathfrak{Y}^{(2)}_{ji}, \mathfrak{Y}^{(3)}_{ji}\right) \\ &= \left(\zeta_1 * \mathfrak{Y}^{(1)}_{ji} \tilde{\oplus} \zeta_2 * \mathfrak{Y}^{(2)}_{ji} \tilde{\oplus} \zeta_3 * \mathfrak{Y}^{(3)}_{ji}\right). \end{aligned}$$

Aggregated PF decision matrix given in Table 7.

TABLE 4. Assessment matrix acquired from D_1.

	C_1	C_2	C_3	C_4
A_1	(0.420, 0.250, 0.150)	(0.350, 0.250, 0.100)	(0.350, 0.210, 0.170)	(0.310, 0.240, 0.210)
A_2	(0.350, 0.150, 0.220)	(0.330, 0.310, 0.210)	(0.290, 0.310, 0.140)	(0.430, 0.250, 0.150)
A_3	(0.200, 0.170, 0.240)	(0.150, 0.280, 0.240)	(0.250, 0.230, 0.150)	(0.270, 0.380, 0.210)
A_4	(0.340, 0.120, 0.150)	(0.480, 0.260, 0.120)	(0.470, 0.180, 0.230)	(0.330, 0.260, 0.230)
A_5	(0.160, 0.370, 0.130)	(0.480, 0.260, 0.190)	(0.280, 0.310, 0.320)	(0.110, 0.170, 0.330)
A_6	(0.150, 0.300, 0.150)	(0.400, 0.200, 0.150)	(0.200, 0.150, 0.200)	(0.150, 0.350, 0.250)

TABLE 5. Assessment matrix acquired from D_2.

	C_1	C_2	C_3	C_4
A_1	(0.340, 0.330, 0.120)	(0.560, 0.120, 0.130)	(0.340, 0.140, 0.110)	(0.510, 0.310, 0.110)
A_2	(0.510, 0.230, 0.130)	(0.160, 0.350, 0.220)	(0.370, 0.420, 0.120)	(0.450, 0.110, 0.120)
A_3	(0.240, 0.120, 0.310)	(0.170, 0.470, 0.260)	(0.250, 0.370, 0.240)	(0.250, 0.130, 0.140)
A_4	(0.130, 0.240, 0.260)	(0.280, 0.330, 0.140)	(0.270, 0.250, 0.340)	(0.250, 0.230, 0.360)
A_5	(0.360, 0.200, 0.230)	(0.280, 0.240, 0.350)	(0.280, 0.130, 0.330)	(0.150, 0.250, 0.330)
A_6	(0.160, 0.370, 0.130)	(0.480, 0.260, 0.190)	(0.280, 0.310, 0.320)	(0.110, 0.170, 0.330)

TABLE 6. Assessment matrix acquired from D_3.

	C_1	C_2	C_3	C_4
A_1	(0.470, 0.140, 0.110)	(0.340, 0.250, 0.200)	(0.550, 0.300, 0.110)	(0.420, 0.130, 0.110)
A_2	(0.330, 0.240, 0.140)	(0.140, 0.220, 0.330)	(0.230, 0.150, 0.420)	(0.230, 0.430, 0.240)
A_3	(0.370, 0.260, 0.270)	(0.130, 0.210, 0.540)	(0.230, 0.150, 0.220)	(0.260, 0.220, 0.430)
A_4	(0.220, 0.460, 0.130)	(0.250, 0.410, 0.240)	(0.410, 0.150, 0.140)	(0.260, 0.440, 0.130)
A_5	(0.140, 0.150, 0.460)	(0.270, 0.450, 0.160)	(0.120, 0.410, 0.260)	(0.210, 0.110, 0.430)
A_6	(0.580, 0.250, 0.130)	(0.430, 0.320, 0.150)	(0.230, 0.310, 0.210)	(0.280, 0.470, 0.170)

Step 4: There is no cost type feature, hence the normalised decision matrix is $\Gamma_N = \left(\aleph_{ji}^N\right)_{n\times m} = \left(\breve{\eta}_{ji}, \breve{\rho}_{ji}, \breve{\aleph}_{ji}\right)_{5\times 4}$, given in Table 8.

Step 5: Construct the score matrix, by utilizing the SF of PFNs as $\Psi = \left(\breve{\eta}^{\daleth}\left(\aleph_{ji}^N\right)\right)_{6\times 4}$.

$$
\begin{array}{c}
\\ A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \\ A_6
\end{array}
\begin{array}{c}
\begin{array}{cccc} C_1 & C_2 & C_3 & C_4 \end{array} \\
\begin{pmatrix}
0.647409 & 0.636285 & 0.664695 & 0.652938 \\
0.620746 & 0.464140 & 0.546148 & 0.597231 \\
0.498141 & 0.396716 & 0.520744 & 0.509427 \\
0.521758 & 0.576489 & 0.582377 & 0.532917 \\
0.467515 & 0.554385 & 0.447495 & 0.391809 \\
0.575705 & 0.641226 & 0.498895 & 0.464264
\end{pmatrix}
\end{array}
$$

Step 6: Consider that the DMs provide the following partial weight details about the attribute weights:

$$\Psi = 0 \leq \Re^{\gamma}{}_1 \leq 0.45,\ 0.10 \leq \Re^{\gamma}{}_2 \leq 0.50,$$
$$0.10 \leq \Re^{\gamma}{}_3 \leq 0.35,\ 0.70 \leq \Re^{\gamma}{}_4 \leq 0.85$$

Relying on this data, the following optimization framework can be developed:

$$
\begin{aligned}
Max\ \ g &= 0.647409\Re^{\gamma}{}_1 + 0.620746\Re^{\gamma}{}_1 + 0.498141\Re^{\gamma}{}_1 \\
&\quad + 0.521758\Re^{\gamma}{}_1 + 0.467515\Re^{\gamma}{}_1 + 0.575705\Re^{\gamma}{}_1 \\
&\quad + 0.636285\Re^{\gamma}{}_2 + 0.464140\Re^{\gamma}{}_2 + 0.396716\Re^{\gamma}{}_2 \\
&\quad + 0.576489\Re^{\gamma}{}_2 + 0.554385\Re^{\gamma}{}_2 + 0.641226\Re^{\gamma}{}_2 \\
&\quad + 0.664695\Re^{\gamma}{}_3 + 0.546148\Re^{\gamma}{}_3 + 0.528909\Re^{\gamma}{}_3 \\
&\quad + 0.582377\Re^{\gamma}{}_3 + 0.447495\Re^{\gamma}{}_3 + 0.498895\Re^{\gamma}{}_3 \\
&\quad + 0.652938\Re^{\gamma}{}_4 + 0.597231\Re^{\gamma}{}_4 + 0.509427\Re^{\gamma}{}_4 \\
&\quad + 0.532917\Re^{\gamma}{}_4 + 0.391809\Re^{\gamma}{}_4 + 0.464264\Re^{\gamma}{}_4
\end{aligned}
$$

such that,

$$
\begin{aligned}
&0 \leq \Re^{\gamma}{}_1 \leq 0.45,\ 0.10 \leq \Re^{\gamma}{}_2 \leq 0.50,\ 0.10 \leq \Re^{\gamma}{}_3 \leq 0.35, \\
&0.70 \leq \Re^{\gamma}{}_4 \leq 0.85,\ \Re^{\gamma}{}_1 + \Re^{\gamma}{}_2 + \Re^{\gamma}{}_3 + \Re^{\gamma}{}_4 = 1, \\
&\Re^{\gamma}{}_1, \Re^{\gamma}{}_2, \Re^{\gamma}{}_3, \Re^{\gamma}{}_4 \geq 0.
\end{aligned}
$$

By solving this model we get, $\Re^{\gamma}{}_1 = 0.10, \Re^{\gamma}{}_2 = 0.10, \Re^{\gamma}{}_3 = 0.10, \Re^{\gamma}{}_4 = 0.70$

Step 7: Evaluate the aggregated weighted PF decision matrix by using proposed AOs given by Table 9.

Step 8: Compute the score values of all alternatives.

$$
\begin{aligned}
\breve{\eta}^{\daleth}(A_1) &= 0.652338 \\
\breve{\eta}^{\daleth}(A_2) &= 0.579894 \\
\breve{\eta}^{\daleth}(A_3) &= 0.497076 \\
\breve{\eta}^{\daleth}(A_4) &= 0.541342 \\
\breve{\eta}^{\daleth}(A_5) &= 0.417550 \\
\breve{\eta}^{\daleth}(A_6) &= 0.493467
\end{aligned}
$$

At the end, the final ranking will be

$$A_1 \succ A_2 \succ A_4 \succ A_3 \succ A_6 \succ A_5.$$

As a result, option A_1's status is the most suitable.

TABLE 7. Aggregated PF decision matrix.

	C_1	C_2
A_1	(0.422189, 0.225431, 0.127371)	(0.421659, 0.204735, 0.149089)
A_2	(0.402705, 0.215718, 0.161213)	(0.195187, 0.296201, 0.266906)
A_3	(0.292668, 0.193871, 0.296387)	(0.160519, 0.322402, 0.367088)
A_4	(0.234194, 0.285582, 0.190678)	(0.326241, 0.35182, 0.173264)
A_5	(0.220777, 0.236234, 0.285746)	(0.33686, 0.329097, 0.228091)
A_6	(0.316179, 0.364609, 0.164769)	(0.449144, 0.269268, 0.166692)
	C_3	C_4
A_1	(0.470899, 0.240426, 0.14151)	(0.450173, 0.248104, 0.144297)
A_2	(0.319708, 0.287495, 0.227413)	(0.380889, 0.262379, 0.186428)
A_3	(0.260008, 0.244701, 0.218519)	(0.297395, 0.247103, 0.27854)
A_4	(0.393162, 0.197934, 0.228407)	(0.296494, 0.371093, 0.230661)
A_5	(0.218022, 0.281204, 0.323031)	(0.162284, 0.168617, 0.378667)
A_6	(0.256326, 0.274761, 0.258537)	(0.195949, 0.350987, 0.26742)

TABLE 8. Normalized PF decision matrix.

	C_1	C_2
A_1	(0.422189, 0.225431, 0.127371)	(0.421659, 0.204735, 0.149089)
A_2	(0.402705, 0.215718, 0.161213)	(0.195187, 0.296201, 0.266906)
A_3	(0.292668, 0.193871, 0.296387)	(0.160519, 0.322402, 0.367088)
A_4	(0.234194, 0.285582, 0.190678)	(0.326241, 0.35182, 0.173264)
A_5	(0.220777, 0.236234, 0.285746)	(0.33686, 0.329097, 0.228091)
A_6	(0.316179, 0.364609, 0.164769)	(0.449144, 0.269268, 0.166692)
	C_3	C_4
A_1	(0.470899, 0.240426, 0.14151)	(0.450173, 0.248104, 0.144297)
A_2	(0.319708, 0.287495, 0.227413)	(0.380889, 0.262379, 0.186428)
A_3	(0.260008, 0.244701, 0.218519)	(0.297395, 0.247103, 0.27854)
A_4	(0.393162, 0.197934, 0.228407)	(0.296494, 0.371093, 0.230661)
A_5	(0.218022, 0.281204, 0.323031)	(0.162284, 0.168617, 0.378667)
A_6	(0.256326, 0.274761, 0.258537)	(0.195949, 0.350987, 0.26742)

TABLE 9. Aggregated weighted PF decision matrix.

A_1	(0.447838, 0.241089, 0.143162)
A_2	(0.356566, 0.266209, 0.196778)
A_3	(0.278908, 0.250558, 0.284755)
A_4	(0.306909, 0.344608, 0.224225)
A_5	(0.192303, 0.203517, 0.357203)
A_6	(0.234438, 0.342150, 0.247505)

Figure 18 presents a complete framework to demonstrate step-by-step process of Data processing, Feature selection, and Features evaluation using Machine Learning algorithms, to design decision matrix that can support in ranking the Machine Learning algorithms based on their performances.

VII. CONCLUSION AND FUTURE WORK

In this research work, we, first, employed six machine learning algorithms to predict energy consumption of smart home appliances. The dataset used in this research contains energy consumption values of various home appliances as well as total energy consumption in the house. This dataset is processed with respect to the contextual information, for instance, weather information. Principal Component Analysis (PCA) is applied on the data for dimensionality reduction using an explained variance of 0.95. We also used Lasso Regression to understand the patterns and features of weather information for smart house micro-climate and its impact on energy consumption of appliances.The evaluation matrix comprises of Mean Absolute Error, Mean Squared Error, and Root Mean Squared Error to evaluate the performance of each employed Machine Learning Model. It is observed from the evaluation matrix that Support Vector Regression, when resampled, outperformed the performance of other models with highest prediction accuracy.

Secondly, in order to validate the proposed results as well as to automate the decision making process, we proposed an automatic decision matrix using fuzzy operators to aggregate all six Machine Learning algorithms. The ranking of best Machine Learning algorithm was determined using score function. In this algorithm, a fairly multicriteria decision making algorithm is developed using fairly AOs with multiple decision makers' evaluations and partial weight information under PFSs. By using this decision-making algorithm, we validate our proposed results. The performance of the model can be improved in the future for better forecast results by gathering accurate weather information from meteorological institution, and by hyper parameter tuning the model.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

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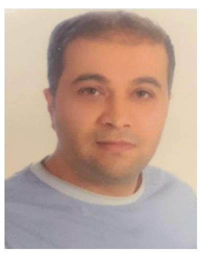

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