Smart Energy Management System of Using Machine Learning

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Abstract- Smart Energy Management Systems (SEMS) are an essential methods of addressing the global issue of inefficient energy usage. This paper provides a solution by proposing the use of machine learning (ML) approaches in the growth of a smart energy system. The system uses features such as request forecasting, optimization control, and business continuity planning support to optimize energy consumption and level out energy consumption fluctuations. The proposed system is powered by the advance technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), and ML. The system uses ML to provide accurate energy estimation for both hourly and day-ahead planning. Tests have shown that the proposed energy management system is able to achieve an accuracy rate of 90.1% and a miss rate of 9.9%. This system is a great way to ensure efficient energy usage, leading to financial savings, better sustainability, and improved quality of life. With its capabilities, the SEMS is a reliable and effective way to manage energy in an ever-changing environment.

Keywords: Smart energy management system (SEMS), Smart System, Machine Learning

1 Introduction

Electrical energy preservation is a stirring concern these days because of dramatically expanding energy requests in India and from one side of the planet to the other. Albeit the advances take knowledge to a higher level, with convincing movements in signal handling and marked calculations created throughout the past 10 years, the root level of energy the board is gotten exclusively as of home energy use, electric burden profiling, and burden checking methods. The principal objective of this paper is to examine the good methodologies that have been surveyed to date and to take care of the burden disaggregation explicitly, criticize the information for enhancement, and produce energy on the board. The entire family utilization is followed by a commonplace meter. The energy providers use these estimations to charge clients for their utilization. These meters measure the information utilizing an unobtrusive testing rate for a solitary fundamental stockpile line since they were made for invoicing. More clever home control and better information granularity are expected to oblige the elements of brilliant lattices. The method for machine load checking, where a meter is attached to every gadget, is called as Intrusive Load Monitoring (I.L.M.) because it needs many conveyed sensors to get the information and a need to interrupt the home and its gadgets. While, on account of Non-Intrusive Load Monitoring (N.I.L.M.), amassed load information is utilized to extricate and distinguish heaps of singular gadgets. The thought in N.I.L.M. is basic; expect to be that two on/off gadgets are associated with a solitary meter, a low-fueled and a powerful one. If neither one of the gadgets is on, the meter doesn't estimate anything; assuming that the low one is on, it estimates a little utilization. On the off chance that the high one is on, it estimates an intense usage; assuming equally are on, it estimates the amount of the little as well as the high-level ones.

Therefore, in this study, they go through sub-meters for the presence of the mind. That is, they set up a metering gadget to evaluate the recent and voltage ingested for each family load and disaggregate the energy utilization of each stack. This paper secures dealing with back the energy use information of every gadget back to the controller that is being spoken with every one of the home gadgets through the ML Algorithm altered in M.A.T.L.A.B. for expecting the client direct of energy use. A GUI is made to enlighten the client on his electrical use, giving multiple decisions like Bill forecast, Budgeting, Protection prerequisites, etc. The client can see energy use assumptions in the two units and charges for the continuous bill cycle, set spending plans, and get reprobation's expecting typical everyday use is extra than the set spending plan, view when contraptions need backing or replacement and view load curves of individual machines. This makes the client more empowered. The simulated intelligence algorithm being used combines thoughts of the Nearest Neighbor Algorithm and Markov Chain. It forecasts the state of machines considering past data and helps in energy the chiefs and protection [1].

The reproduction results highlight that the PSO-based SVM model beats any remaining models utilized in late examinations. For this situation, hyperparameters are tuned, consequently founded on the PSO enhancement calculation. Equipment trial arrangement shows power discussion situation consider the anticipated power and additional dispatch the controller activity based on configurable need decision. In this study, an Intelligent SEMS engineering is proposed for request side energy the board thinking about Renewable sources. The created design has PV-produced information assortment for expectation models, savvy energy the board framework for load planning, and IoT climate for the client to get to the energy subtleties and the executives. The suggested work utilizes an A.I. way to deal with foreseeing exact energy for the day ahead and month-to-month premise. Because of the anticipated data, I.S.E.M.S. arranges the accessible power and dispatch the control activity relying upon the buyer's allocated need for an apparatus [2].

The review presents a full plan and design for applying smart energy, the executive's framework in the mining business no matter what and the innovation of the control framework adjusted because the utilization of O.P.C. information transmission can be executed in various sorts of open pit mines. This study aimed to provide original energy as the board framework foundation for an ordinary excavation site, where the framework can record, screen, and provide insights into various energy and electrical matrix excellence information. The framework proposes a heap determining calculation to foresee the energy request reaction in the open pit mine. The proposed, as well as tried design, will empower the different smart microgrid elements, for example, advancement and burden booking strategies, power shedding, decentralized energy creation through inexhaustible sources as well as energy stockpiling frameworks, as well as the energy review systems are simply utilizing the report age capability [3].

2 Related work

This section features a couple of related undertakings and examinations concerning HEMS and IoT innovation. These works are rules and structure the premise of the proposed framework. The undertaking finished by the framework permits home apparatuses to be controlled and observed through an Android-based application, where the door (Arduino Uno) is associated with gadgets utilizing Ethernet. The door goes about as a miniature web server to make do, control and screen framework parts that empower equipment interface modules to execute their doled-out task utilizing actuators effectively and to report server with set off occasions through sensors. This framework depends vigorously on wired Ethernet LAN association and needs information transmission through Wi-Fi.

Then again, the proposed framework considers energy utilization and age considering ZigBee and PLC-based sustainable power entryway (R.E.G.). The home server assembles energy utilization information through ZigBee and energy age information through the R.E.G. As far as equipment execution, the framework is viewed as perplexing because of the equipment execution for energy age examination [4].

It implies a Home Energy Management System (HEMS) that utilizes Arduino Uno and other cutting-edge fittings to monitor energy in the home in order to address the problem of information transfer through Wi-Fi and reduce the complexity of the system. Depending on client requests from the application, a door can speak with dazzling fittings to turn on or off devices. To execute robotized decisions, nevertheless, an A.I. calculation is still lacking. Essentially, the project relies on LAN (Local Area Network) and WIFI connections that are already set up in the home. It consists of remote energy observing hubs and a server that runs Linux and may be retrieved from the Internet, but the framework is only capable of checking energy use and cannot make any decisions or project information [5].

Before long, independent sun-powered P.V. age will assume a critical part in the power business because of developing worry over petroleum product use. Thus, anticipating P.V 75 is fundamental. yield information precisely and plan the heap/machine activity at the buyer's end for effective use. Multiple techniques may be deemed for demonstrating sun-based irradiance relying upon the accessibility of dataset length, boundaries utilized, and utilization subtleties. There are many benefits of precise sustainable gauging for utilities and energy shoppers 80, like minimal expense, dispatch capacity, and efficiency. Checking the solid and secure power framework activity fundamentally relies upon day-ahead arranging with sustainable age gauge and request utilization data. Precise determining data from sustainable power generators assists the energy area with limiting power vacillations and keeping up with the framework's general unwavering quality. 85 Further, observing the conjecture data may likewise assist the energy makers with saving the framework's wellbeing [6].

Then again, a few works are done toward conveying the interest side energy of the executive's framework. The Demand Response (D.R.) occasion permits the buyer to transform their energy utilization design considering the hour of use and Utility Tari to stay away from top use. In the writing, writers centre around planning and controlling in-home apparatuses to 110 give monetary benefits to private energy executives. In ongoing work, the creators present a coordinated climate to deal with machine interest, i.e., HVAC in a business building. Consequently, to keep up with personal client fulfilment and machine need [7].

Particle Swarm Optimization (PSO) strategy is utilized for ideal boundaries of ANN and S.V.R. The PSO-based boundary tuning procedure shows critical outcomes contrasted with the cutting-edge techniques for the given data set. Because of best in class, to oversee request side machines efficiently without restricting client solace, there is a requirement for more exact environmentally friendly power expectation models. In this specific circumstance, fostering a definite expectation model in [8] depends on a few high-level Machine Learning strategies. For efficient energy the board framework, a client configurable dynamic need task highlight is empowered related to an IoT climate. The proposed design is assessed at the research facility level trial arrangement, which shows a high-level S.E.M.S. framework with an exact expectation model, upgraded load procedure, and dependable correspondence. Further, on obtaining metering information broadly, investigating research on the administration of energy systems is conceivable. A few exploration clusters are presently investigating continuous energy the executives' arrangements, broad information examination A.I., and energy cost arrangements.

Most of the techniques have been utilized while utilizing and creating different smart and intelligent structures like ML techniques [9-11], Fuzzy Inference systems [12],cloud computing [13-14] and round robin scheduling [15] that may offer assistance in constructing emerging explanations for the increasing disputes in designing intelligent cloud-based checking management systems.

3 Proposed Methodology

Energy executives assume a key role in controlling and reducing energy consumption in the industrial sector, as well as in the economic advancement of a nation. Most existing home energy management systems are designed to plan for energy savings and user comfort by partially controlling smart devices through a local awareness strategy and intelligently modifying the setpoints. As such, Renewable Energy (RE) sources, including geothermal, wind, solar, biomass and others, have become potential energy development options. In the domain of green power-related applications such as energy generation and integration, consumption and demand analysis, ML approaches such as ANN have been gaining traction. In this study, an ANN-based ML approach is proposed for improved energy management. The ANN model is based on the concepts of energy efficiency and user comfort in order to optimize the energy consumption and minimize user discomfort.

The ANN model consists of two major components: input data layer and output layer. The input layer consists of various parameters such as energy demand, ambient temperature, energy price and user preferences. These parameters are then processed in the ANN model to generate suitable control signals for the energy execution system. The output layer consists of control signals for lighting and HVAC systems, which help in minimizing energy consumption and user discomfort.

The proposed ANN-based energy management system is further tested using a real-time dataset from the University of Michigan. The results from the tests demonstrate a significant reduction in energy consumption and user discomfort levels. It is also shown that the ANN-based system outperforms traditional methods in both energy savings and user comfort levels. These results indicate the promising potential of ANN-based energy management systems for efficient energy management.

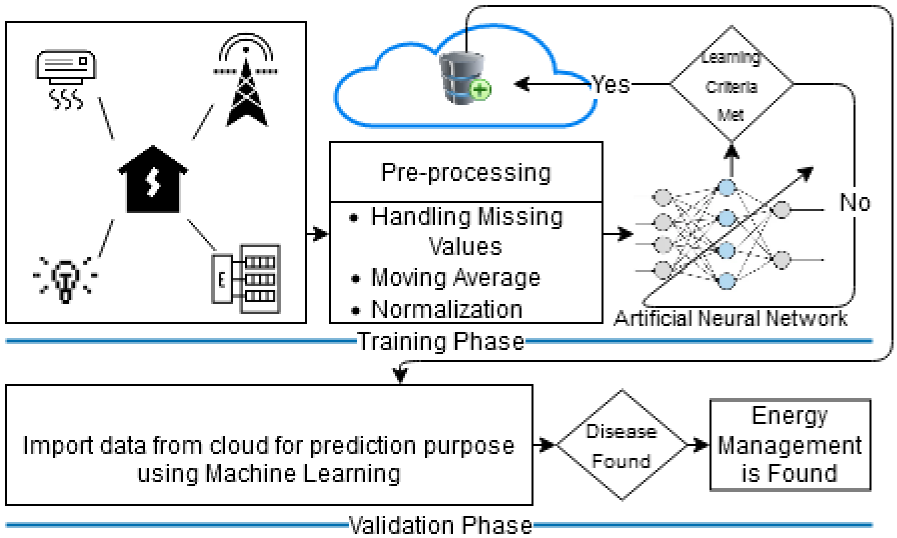

Figure 1: Proposed Energy Management Model

Figure 1 indicates that energy data is gathered from multiple input sensors, and data is passed through the preprocessing layer to minimize the noise through wireless communication. After the preprocessing, the preprocessed information is forwarded to train using an artificial neural network-based machine learning approach. The information layer stowed away layer, in the expansion yield layer is used in ANN engineering, in which each neuron existing in the secret layer has an actuation capability like f(x)=Sigmoid(x). The sigmoid function for input is created as

$$\text{ђ}_{j} = Y_1 + \sum_{i=1}^{m}(\omega_{ij} * r_i) \tag{1}$$

$$\text{ց}_{j} = \frac{1}{1+e^{-\text{ђ}_{j}}} \quad where\ j = 1, 2, 3 \ldots n \tag{2}$$

Input is drived from the output layer

$$\text{ђ}_{k} = Y_2 + \sum_{j=1}^{n}(v_{jk} * \text{ց}_{j}) \tag{3}$$

Output layer activation function

$$\text{ց}_{k} = \frac{1}{1+e^{-\text{ђ}_{k}}} \quad where\ k = 1, 2, 3 \ldots r \tag{4}$$

Error in backpropagation expressed as Equation (5)

$$E = \frac{1}{2}\sum_{k}(t_k - \text{ց}_{k})^2 \tag{5}$$

Where t_k $r$represents the desired output and out_k As a calculated output, Equation (6) rate of change in weight for the output layer is recorded as.

$$\Delta W \propto -\frac{\partial E}{\partial W}$$

$$\Delta v_{j,k} = -\epsilon \frac{\partial E}{\partial v_{j,k}} \tag{6}$$

Chain rule method

$$\Delta v_{j,k} = -\epsilon \frac{\partial E}{\partial \text{ց}_{k}} \times \frac{\partial \text{ց}_{k}}{\partial \text{ђ}_{k}} \times \frac{\partial \text{ђ}_{k}}{\partial v_{j,k}} \tag{7}$$

When substituting Equation (7), the value of weight changeover can be

$$\Delta v_{j,k} = \epsilon(t_k - \text{ց}_{k}) \times \text{ց}_{k}(1 - \text{ց}_{k}) \times (\text{ց}_{j})$$

$$\Delta v_{j,k} = \epsilon \xi_k \text{ց}_{j} \tag{8}$$

Where

$$\boldsymbol{\xi_k} = (\boldsymbol{t_k} - \mathrm{g}_{\boldsymbol{k}}) \times \mathrm{g}_{\boldsymbol{k}}(\mathbf{1} - \mathrm{g}_{\boldsymbol{k}})$$
$$\Delta\boldsymbol{\omega_{i,j}} \propto - \left[\sum_k \frac{\partial \boldsymbol{E}}{\partial \mathrm{g}_{\boldsymbol{k}}} \times \frac{\partial \mathrm{g}_{\boldsymbol{k}}}{\partial \text{ƀ}_{\boldsymbol{k}}} \times \frac{\partial \text{ƀ}_{\boldsymbol{k}}}{\partial \mathrm{g}_{\boldsymbol{j}}}\right] \times \frac{\partial \mathrm{g}_{\boldsymbol{j}}}{\partial \text{ƀ}_{\boldsymbol{j}}} \times \frac{\partial \text{ƀ}_{\boldsymbol{j}}}{\partial \boldsymbol{\omega_{i,j}}}$$
$$\Delta\boldsymbol{\omega_{i,j}} = -\boldsymbol{\epsilon} \left[\sum_k \frac{\partial \boldsymbol{E}}{\partial \mathrm{g}_{\boldsymbol{k}}} \times \frac{\partial \mathrm{g}_{\boldsymbol{k}}}{\partial \text{ƀ}_{\boldsymbol{k}}} \times \frac{\partial \text{ƀ}_{\boldsymbol{k}}}{\partial \mathrm{g}_{\boldsymbol{j}}}\right] \times \frac{\partial \mathrm{g}_{\boldsymbol{j}}}{\partial \text{ƀ}_{\boldsymbol{j}}} \times \frac{\partial \text{ƀ}_{\boldsymbol{j}}}{\partial \boldsymbol{\omega_{i,j}}}$$
$$\Delta\boldsymbol{\omega_{i,j}} = \boldsymbol{\epsilon} \left[\sum_k (\boldsymbol{t_k} - \mathrm{g}_{\boldsymbol{k}}) \times \mathrm{g}_{\boldsymbol{k}}(\mathbf{1} - \mathrm{g}_{\boldsymbol{k}}) \times (\boldsymbol{\nu_{j,k}})\right] \times \mathrm{g}_{\boldsymbol{k}}(\mathbf{1} - \mathrm{g}_{\boldsymbol{k}}) \times \boldsymbol{r_i}$$
$$\Delta\boldsymbol{\omega_{i,j}} = \boldsymbol{\epsilon} \left[\sum_k (\boldsymbol{t_k} - \mathrm{g}_{\boldsymbol{k}}) \times \mathrm{g}_{\boldsymbol{k}}(\mathbf{1} - \mathrm{g}_{\boldsymbol{k}}) \times (\boldsymbol{\nu_{j,k}})\right] \times \mathrm{g}_{\boldsymbol{j}}(\mathbf{1} - \mathrm{g}_{\boldsymbol{j}}) \times \boldsymbol{r_i}$$
$$\Delta\boldsymbol{\omega_{i,j}} = \boldsymbol{\epsilon} \left[\sum_k \boldsymbol{\xi_k} (\boldsymbol{\nu_{j,k}})\right] \times \mathrm{g}_{\boldsymbol{j}}(\mathbf{1} - \mathrm{g}_{\boldsymbol{j}}) \times \boldsymbol{r_i}$$
$$\Delta\boldsymbol{\omega_{i,j}} = \boldsymbol{\epsilon\xi_j}\, \boldsymbol{r_i} \tag{9}$$

where

$$\boldsymbol{\xi_j} = \left[\sum_k \boldsymbol{\xi_k} (\boldsymbol{\nu_{j,k}})\right] \times \mathrm{g}_{\boldsymbol{j}}(\mathbf{1} - \mathrm{g}_{\boldsymbol{j}})$$

output and hidden layer is displayed in Equation (10), that is renewing the weight and bias among them

$$\boldsymbol{\nu^{+}_{j,k}} = \boldsymbol{\nu_{j,k}} + \lambda_F \Delta\boldsymbol{v_{j,k}} \tag{10}$$

Updating weight and bias between the input layer and the hidden layer is shown in Equation (11)

$$\boldsymbol{\omega^{+}_{i,j}} = \boldsymbol{\omega_{i,j}} + \lambda_F \Delta\boldsymbol{\omega_{i,j}} \tag{11}$$

λ_F is the learning rate of the suggested model. Convergence of the suggested model upon the careful selection of λ_F.

After training, it is then checked whether the learning criteria are happened. In the situation of No, the training process is re-trained, but in the situation of Yes, the trained result is collected in the cloud. Then the prepared data is introduced from the cloud for forecast using the ANN approach based on machine learning. It is checked whether energy management is found or not in the validation phase. The operation is discarded in the case of no, whereas in the case of yes, the notification will state that the energy management is detected.

4 Simulation Results

This research is introducing a smart energy management system [16] utilizing a machine learning technique while constructing and improving a better and further efficient model. The suggested ANN-based technique is employed to a dataset collected from the U.C.I. machine learning data repository. The proposed ANN-based method is used in many instances 24673 to predict energy management. Besides, the dataset is parted into preparing is of 70% (17271 examples) as well as 30% (15196 pieces) for the uncovered preparation as well as approval purposes. Various boundaries utilized for execution computation with different measurements are subsequent by the recipes:

$$Sensitivity = \frac{\sum True\ Positive}{\sum Condition\ Positive} \tag{16}$$
$$Specificity = \frac{\sum True\ Negative}{\sum Condition\ Negative} \tag{17}$$
$$Accuracy = \frac{\sum True\ Positive + \sum True\ Positive}{\sum Total\ Population} \tag{18}$$
$$Miss - Rate = \frac{\sum False\ Negative}{\sum Condition\ Positive} \tag{19}$$
$$Fallout = \frac{\sum False\ Positive}{\sum Condition\ Negative} \tag{20}$$
$$Likelihood\ Positive\ Ratio = \frac{\sum True\ Positive\ Ratio}{\sum False\ Positive\ Ratio} \tag{21}$$
$$Likelihood\ Negative\ Ratio = \frac{\sum True\ Positive\ Ratio}{\sum False\ Positive\ Ratio} \tag{22}$$
$$Positive\ Predictive\ Value = \frac{\sum True\ Positive}{\sum\ Predicted\ Condition\ Positive} \tag{23}$$
$$Negative\ Predictive\ Value = \frac{\sum True\ Negative}{\sum\ Predicted\ Condition\ Negative} \tag{24}$$

Table 1: Proposed model training using ANN

Suggested Model Training

Input	Total samples (17271)	Result	
	Expected output	Forecasted Positive	Forecasted Negative
		True Positive (T.P.)	False Positive (F.P.)
	10117 Positive	9421	696
		False Negative (F.N.)	True Negative (TN)
	7154 Negative	622	6532

It is presented in table 1 that the suggested system predicts energy management in the training period. 17271 samples are utilized in training, distributed into 10117, 7154 positive, and negative samples. 9421 true positives are effectively forecasted, and no energy management is found, but 696 records are wrongly forecasted as negatives, highlighting energy management is found. Similarly, 7154 samples are taken, with negative indicating energy management is identified and positive showing no energy management. With 6532 samples correctly identified as negative showing, energy management is identified and 622 samples being wrongly predicted as positive, representing no energy management is identified despite the presence of energy management.

Table 2: Proposed model validation using ANN

Proposed Model Validation			
Input	Samples (7402)	Result	
	Expected output	Forecasted Positive	Forecasted Negative
		TP	FP
	4116 Positive	3725	391
		FN	TN
	3286 Negative	340	2946

It is seen in table 1 that the suggested system predicts energy management during the training period. 7402 samples are utilized throughout training, distributed into 4116, 3286 positive, and negative samples. 3725 true positives are effectively forecast, and no energy management is identified, but 391 records are wrongly forecast as negatives, presenting energy management is identified. Similarly, 3286 samples are taken, with negative highlighting energy management is identified as well as positive showing no energy management. With 2946 samples correctly identified as negative, showing energy management is identified, and 340 samples wrongly forecast as positive, representing no energy management is identified despite the presence of energy management.

Table 3: Proposed model performance in training and validation (SVM)

SVM	Accuracy	Sensitivity T.P.R.	Specificity TNR	Miss-Rate (%) F.N.R.	Fall-out F.P.R.	LR+	LR-	PPV (Precision)	N.P.V.
Training	0.923	0.938	0.903	0.076	0.096	9.77	0.084	0.931	0.913
Validation	0.901	0.916	0.882	0.098	0.117	7.83	0.111	0.905	0.896

It is observed in Table 3 (ANN) that throughout training, the accuracy of the suggested system in words of accuracy sensitivity, specificity, miss rate, and precision gives 0.923, 0.938, 0.903, 0.076, and 0.931, respectively. In addition, the suggested system throughout training gives 0.096, 9.77, 0.084, and 0.913, and during validation, 0.117, 7.83, 0.111, and 0.896 in terms of fall out likelihood positive ratio, likelihood negative ratio, as well as negative predictive value, respectively. And during validation, the suggested model provides 0.901, 0.916, 0.882, 0.098, as well as 0.905 in terms of accuracy sensitivity, specificity, miss rate, and precision, respectively.

Table 4: Comparison of the proposed approach with previous research work

Approaches	Accuracy	Miss-rate
Linear Regression [17]	68.58	31.42
Polynomial regression [17]	76.87	23.13
Decision Tree regression [17]	81.33	18.67
Deep Extreme Learning Machine [17]	84.01	15.99
Proposed Energy Management System	90.1	9.9

Table. 4 shows a comparison between the previous approaches and the proposed model. The proposed model attained 90.1 accuracies for predicting energy management better than the existing approaches.

5 Conclusion

Energy management systems have develop progressively valuable in currently because of the emergence of renewable energy sources. These sources tend to be irregular and unpredictable, creating unique challenges for energy management. The proposed research seeks to address this issue by developing an ANN-based ML approach for predicting energy management. This approach has already been applied and proven to have a 90.1% accuracy and 9.9% miss-rate, outperforming existing methods. The ANN-based technique is expected to be able to effectively handle the unconventional and unpredictable nature of renewable energy resources. This research will investigate the effectiveness of ANN-based learning for energy management prediction, and the findings will be used to improve the accuracy and reliability of current energy management systems.

6 Limitations and Future Directions

The most significant limitation of an intelligent energy management system is its reliance on data. To create reliable predictions, ML algorithms must be trained with accurate, up-to-date information. If the data used is of poor quality or out of date, the results of the ML models will also be inaccurate. Additionally, if the data is not representative of the energy system being managed, the ML models may not be able to accurately identify patterns and trends. Another limitation of an intelligent energy management system is its ability to identify potential efficiency gains. While ML algorithms can accurately detect patterns in energy use, they may not be able to identify potential improvements that could lead to cost savings. Human insight is still needed for this task, which limits the effectiveness of an IEMS.

Finally, intelligent energy management systems may have difficulty accurately predicting future energy needs. ML algorithms can detect patterns in energy use, but they may not be able to identify changes in external factors that could have an impact on future energy needs. For example, an intelligent energy management system may not be able to accurately predict shifts in consumer demand or changes in weather patterns.

In order for an intelligent energy management system to be effective, there are certain directions for future research that must be considered. Today, the significant areas of study is improving the accuracy of ML algorithms. In order to make reliable predictions, ML models must be trained with accurate, up-to-date data. The study would be directed to enhance the quality of data used for training ML algorithms.

Other areas of research that should be explored include increasing the ability of an intelligent EMS to identify potential efficiency gains. By developing more sophisticated algorithms, an intelligent energy management system may be able to identify more potential improvements that could lead to cost savings. Finally, study should be done to enhance the ability of intelligent EMSs to accurately predict future energy.

7 References

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