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Machine learning methods for energy sector in internet of things

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ABSTRACT

This research paper focuses on exploring machine learning studies and conducting a comparative analysis of their advantages, disadvantages, implementation environments, and algorithms. A key aspect of the study involves evaluating the energy efficiency using machine learning algorithms to predict energy consumption. Additionally, a feature selection algorithm is employed to rank the features, with the highest-ranking feature identified as one of the most significant. The experimentation is conducted using the Weka tool, incorporating several machine learning algorithms such as linear regression, k-nearest neighbors, decision stump, radial basis function (RBF) network, and isotonic regression. The RBF algorithm, which relies on RBF, shares similarities with neural network algorithms. Results indicate a minimum error value of 1.546 for cooling load and 1.364 for heating load. The random forest algorithm emerges as the most suitable choice within the context of this study.

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1. INTRODUCTION

The realm of information technology is constantly evolving, particularly in terms of communication and connectivity across various locations and timeframes. The internet of things (IoT) refers to the interconnectedness and communication between diverse devices [1], [2]. Within the IoT framework, a multitude of valuable information is collected and utilized in smart grid applications [3]. As researchers strive to implement IoT-based networks in practical scenarios [4], an area of focus lies in the prediction and optimization of electricity consumption in residential buildings [5]. The escalating global energy demand resulting from population growth has become a pressing concern for electricity companies, emphasizing the significance of accurate electricity consumption forecasting. Failure to effectively manage energy consumption may lead to energy shortages in the coming years. To address this issue, two approaches are commonly considered: increasing energy production and maximizing the utilization of existing energy resources. While energy production is a costly and resource-intensive solution, employing preventive measures to optimize available energy resources presents a viable alternative [6].

Undoubtedly, the advent of the IoT has had far-reaching implications in our daily lives, reshaping both our environment and society at large. Communication systems researchers often prioritize the communication aspects of the IoT, mistakenly overlooking other crucial factors [7]. The IoT serves as a pivotal source of novel data, and data science plays a crucial role in enhancing the intelligence of IoT applications. Data science integrates various scientific disciplines to uncover patterns and insights through techniques like data mining and machine learning. Different data mining models such as neural networks, classification, and clustering methods are employed to address diverse problems based on data characteristics [8]. In the context of the IoT, the industrial internet of things (IIoT) emerges as a significant field applicable to power plants [9], while also proving useful in detecting malware within enterprise information systems [10]. By enabling seamless communication between a multitude of computers, individuals, data, and processes, the IoT holds immense potential across several domains, enhancing quality and efficiency in areas such as medical services, smart cities, agriculture, and energy [10]–[13].

This article focuses on the identification and comparison of the benefits and drawbacks associated with various machine learning and deep learning methods in the context of the IoT and the energy sector. Additionally, it explores the existing challenges within this domain. Figure 1 provides a thematic classification of machine learning and deep learning applications specific to IoT and the energy sector.

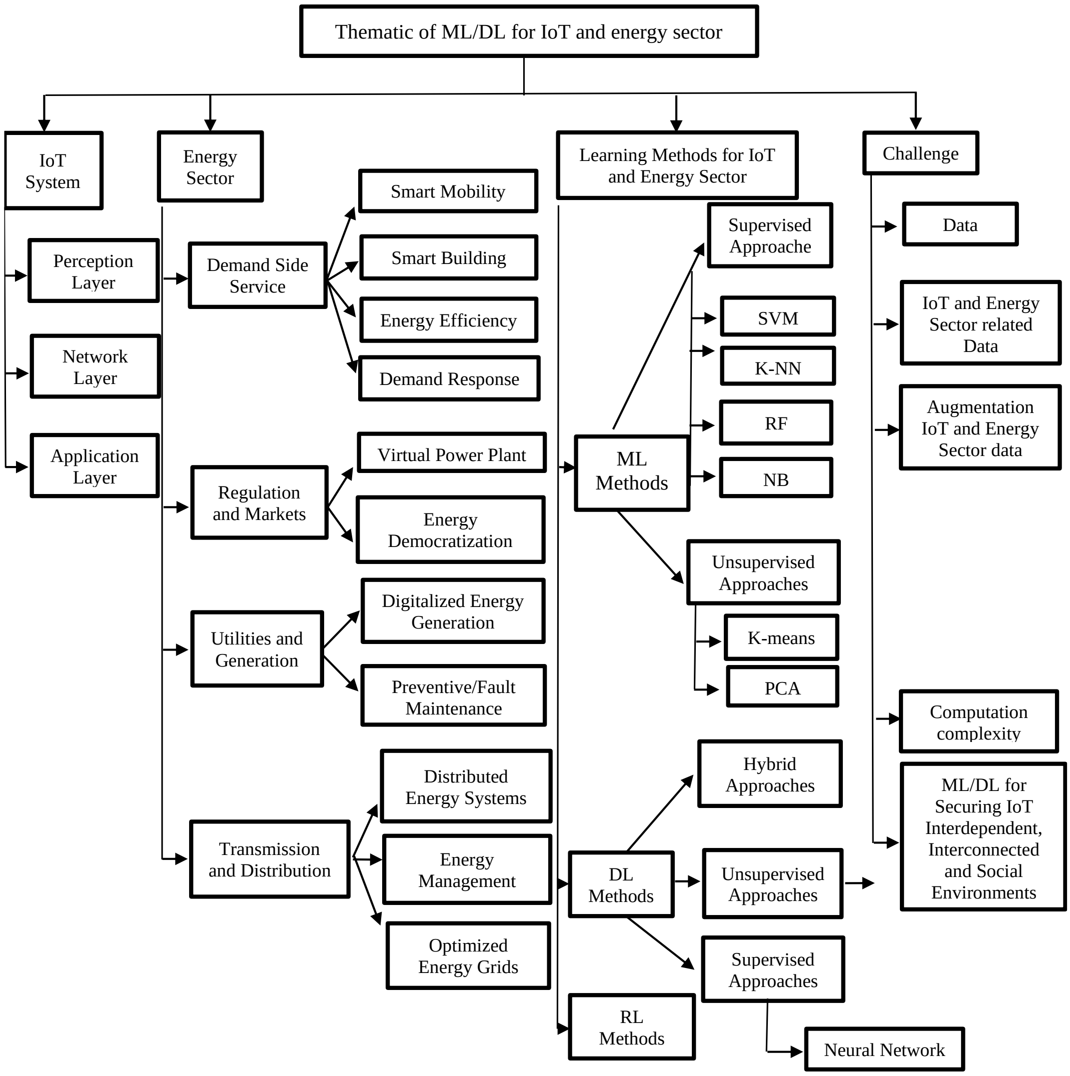

Figure 1. Thematic taxonomy of ML/DL for IoT and energy sector

Mahdavinejad *et al.* [8] carried out an in-depth study on the IoT, with a specific emphasis on addressing the unique challenges associated with IoT data in smart cities. The study extensively evaluated various machine learning methods and aimed to provide a comprehensive classification of algorithms that can effectively extract valuable insights from data. In essence, this classification facilitates the identification of the most suitable algorithm for specific problem domains, enabling the extraction of higher-level information. Overall, the study's findings indicate that, in the context of smart city traffic data, the support vector machine (SVM) method is widely applicable and highly effective.

Shah *et al*. [14] conducted on a research venture centered around the IoT. Their goal was to investigate different strategies to enhance energy efficiency while taking into account factors such as thermal comfort, visual comfort, and air quality. Through the utilization of genetic and artificial neural network algorithms, the researchers were able to pinpoint the crucial aspects that impact energy consumption and efficiently optimize energy utilization within smart homes. Their study accomplished the identification of key factors influencing energy consumption and the successful optimization of energy usage in smart home environments.

Mocanu *et al*. [15] introduced the factored four way conditional restricted Boltzmann machine (FFW-CRBM) approaches as solutions for precise prediction and identification of energy flexibility in smart meter-equipped buildings. They leveraged quadrilateral Boltzmann machines to implement these methods. Subsequently, in the evaluation stage, they applied the algorithm to a dataset encompassing various energy samples. The outcome revealed the algorithm's remarkable capability not only in accurately predicting energy consumption levels but also in estimating real-time energy usage and device utilization.

Ardabili *et al*. [16] conducted the IoT was examined with a specific emphasis on predicting building demand and energy consumption. The researchers evaluated and compared the performance of various machine learning algorithms, such as artificial neural networks, multi-layered perceptrons, and SVM, for this purpose. As a result of their investigation, they successfully identified the most accurate and effective algorithm for predicting energy consumption in buildings.

Motlagh *et al*. [17] delved into the realm of the IoT in their research, specifically investigating its applications within energy systems and smart grids. Their study entailed a thorough analysis of multiple papers, ultimately uncovering the potential of IoT applications in boosting energy efficiency. Moreover, they highlighted how IoT facilitates the implementation of specialized communication and sensor technologies tailored specifically for the energy sector.

Yan *et al*. [18] introduced a statistical algorithm called efficient dominator tree construction (EDTC), which aims to evaluate network topology and enhance a low-energy consumption topology control algorithm. Their approach involves utilizing the maximum spanning tree algorithm to establish a reliable backbone topology. To expedite topology construction, they devised an EDTC algorithm based on graph convolutional networks (GCN). In this method, GCN is trained to predict energy consumption levels at network edges, augmenting the basic EDTC algorithm. Through a random correlation experiment, the algorithm's effectiveness was evaluated, revealing that EDTC effectively doubles the network's lifespan. Furthermore, the GCN-based EDTC algorithm yields a significant improvement in energy efficiency, achieving an impressive 99% increase.

Raza *et al*. [19] presented a cost-effective approach for assessing energy dissipation in heating, ventilation, and air conditioning (HVAC) systems based on consumer behavior (CBB-EW). By utilizing temperature and humidity sensors, they developed machine learning models to capture HVAC performance. The CBB-EW method was divided into two components: non-occupant loss (CBB-EW-NOC) and occupation-based loss (CBB-EW-OCC). The authors proposed a technique that leverages HVAC status, motion sensors, and textual information to determine CBB-EW-NOC. Additionally, CBB-EW-OCC was calculated by quantifying the difference between the energy consumed by the HVAC unit in desired thermal settings and the energy controlled by the user. The study also incorporated the use of the predicted mean vote (PMV) model to establish optimal temperature settings for HVAC operation. To evaluate their proposed method, a case study was conducted involving users managing ventilation units. The results demonstrated that the proposed model achieved a high level of accuracy in predicting HVAC status and aided users in identifying energy loss patterns.

Al-Fahdawi [20] introduces an innovative technique that leverages machine learning and IoT devices to enhance energy management in smart buildings. The approach adopts a decision tree algorithm to accurately forecast energy consumption patterns and optimize energy usage accordingly. Notably, the outcomes illustrate that implementing this approach can yield a remarkable reduction in energy consumption by as much as 30%.

Al-Qutayri [21] introduces an advanced approach that harnesses machine learning and IoT devices for efficient energy management in smart homes. The approach employs a support vector regression algorithm to accurately forecast energy consumption and effectively optimize energy usage. The outcomes demonstrate that implementing this approach holds the potential to significantly reduce energy consumption by up to 25%.

Ghazal *et al*. [22] discuss the use of machine learning approaches for sustainable cities using IoT. The authors propose a framework that integrates IoT and machine learning to improve urban sustainability. The advantages of this approach include improved resource management and reduced environmental impact, while the disadvantages include the need for accurate data and potential privacy concerns. The article concludes that the integration of IoT and machine learning can lead to more sustainable and efficient cities.

Zhuang *et al*. [23] present a cutting-edge data-driven predictive control technique designed specifically for smart HVAC systems in IoT-integrated buildings. The method combines time-series forecasting and reinforcement learning to optimize system performance. Extensive testing on a simulated building revealed remarkable enhancements in both energy efficiency and occupant comfort, surpassing the capabilities of conventional control methods. Notable advantages of the approach include improved energy efficiency and occupant comfort. However, it is essential to note that accurate data inputs and ample computational resources are necessary for successful implementation.

2. RESEARCH METHOD

Figure 2 illustrates the proposed framework for this study, which explores the machine learning aspect of energy efficiency. To investigate this aspect, the researchers utilized the energy efficiency data collection, which is readily available on the UCI website [24]. Initially, the introduced dataset underwent evaluation using various machine learning algorithms to predict energy consumption. Subsequently, a feature selection algorithm was employed to rank the features. Features with higher ranks were identified as the best, while those with lower ranks were excluded from consideration. In this study, the amount of heating load, cooling load with the help of linear regression, k-nearest neighbors, decision stump, radial basis function (RBF) network and isotonic regression algorithms are determined. The RBF algorithm is equivalent to the neural network algorithm based on the radial basic functions. Using the correlation attribute eval algorithm in conjunction with the Weka software, the key factors that greatly influence the prediction of heating load and cooling load are identified.

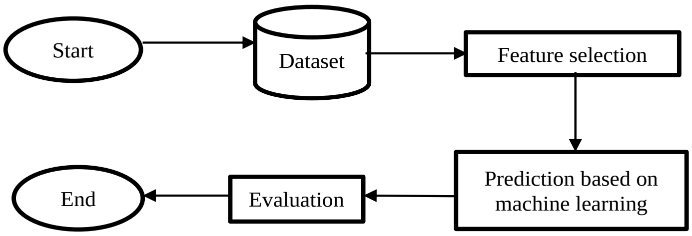

Figure 2. Proposed framework

2.1. Dataset

The data utilized in this study were gathered from a total of 12 diverse buildings, each exhibiting unique characteristics such as glazing region, distribution, and orientation. Simulations encompassing various settings were conducted to explore the impact of these parameters, resulting in a dataset of 768 building shapes. A comprehensive dataset of 768 samples, consisting of 8 attributes, was formed, paving the way for predicting two valuable outcomes. Furthermore, if the responses in this dataset are rounded to the nearest integer, it can also be approached as a multi-class classification problem [25]. The features along with their respective targets are clearly defined in Table 1.

Table 1. Data set and features

Variable description	Input or output variable)
X1	Relative compactness
X2	Surface area
X3	Wall area
X4	Roof area
X5	Overall height
X6	Orientation
X7	Glazing area
X8	Glazing area distribution
Y1	Heating load
Y2	Cooling load

2.2. Feature selection

The evaluation of the significance and effectiveness of the 8 mentioned features is carried out using the correlation attribute eval algorithm. This algorithm allows for assigning weights to the features based on their importance and impact. By doing so, the influential features can be prioritized, while the less significant ones can be disregarded. As a result, the contribution of the less significant features to energy consumption is minimized.

2.3. Evaluation

Three evaluation criteria, namely mean absolute error (MAE) in (1), root mean squared error (RMSE) in (2), and relative absolute error (RAE) in (3), along with root relative squared error (RRSE) in (4), are utilized in this study. These criteria are calculated using their respective formulas described:

$$MAE = \frac{\sum_{n}^{i=1} |y(i) - y'(i)|}{n} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} |y_i - y_i'|^2}{N}} \quad (2)$$

$$RAE = \frac{\sum_{n}^{i=1} |y(i) - y'(i)|}{y(i)} \quad (3)$$

$$RRSE = \sqrt{\frac{\sum_{n}^{i=1} (|y'(i) - y(i)|)^2}{\sum_{n}^{i=1} (y(i) - (mean(y)))}} \quad (4)$$

The formulas mentioned above involve various variables. The variable y_i represents the actual measurement quantity, such as energy consumption, while y_i' stands for the predicted value. The variable N represents the number of samples, and $\bar{y}$ denotes the average value. It's worth noting that the evaluation values presented in this study were calculated using the Weka software.

3. RESULTS AND DISCUSSION

The aim of this study is to forecast the cooling and heating targets. To accomplish this, three algorithms, specifically linear regression, k-nearest neighbors, and random forest, are employed. The errors resulting from the implementation of these algorithms are individually computed for each specific objective. Detailed outcomes of applying these algorithms to the energy efficiency data collection can be referred to in Tables 2 and 3.

Table 2. Assessment of cooling load target result

Evaluation criteria/algorithms	Linear regression	K-NN	Additive regression	RBF network	Isotonic regression
MAE	2.279	3.580	1.546	3.154	3.146
RMSE	3.237	5.522	2.264	4.247	4.239
RAE	26.530	41.676	17.996	36.720	36.632
RRSE	33.988	57.981	23.777	44.590	44.511

Table 3. Assessment of heating load target result

Evaluation criteria/algorithms	Linear regression	K-NN	Additive regression	RBF network	Isotonic regression
MAE	2.092	3.326	1.364	3.514	3.486
RMSE	2.956	5.539	1.758	4.626	4.631
RAE	22.855	36.339	14.907	38.406	38.081
RRSE	29.282	54.855	17.410	45.816	45.867

Upon reviewing Tables 2 and 3, it becomes evident that the MAE criterion stands out as the most effective evaluation metric for both cooling load and heating load targets. The additive regression algorithm emerges as the algorithm with the lowest error rates for both load types. Specifically, the implementation of the random forest algorithm yields a minimum error value of 1.546 for cooling load and 1.364 for heating load. To visually compare the performance of the three algorithms for heating load and cooling load targets, please refer to Figures 3 and 4, respectively.

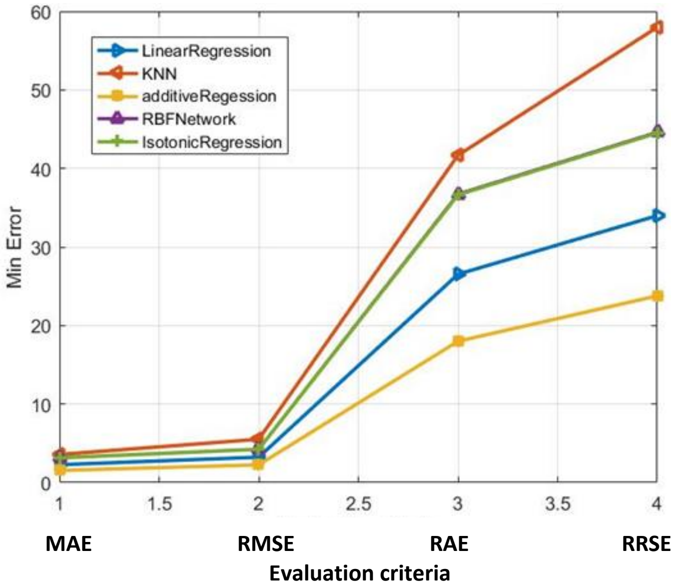

Figure 3. Cooling load target

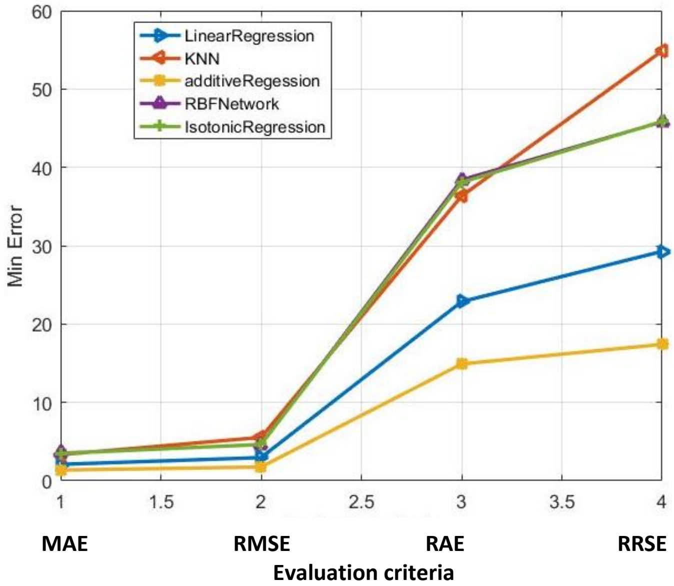

Figure 4. Heating load target

In this study, the correlation attribute eval algorithm is utilized for predicting the optimal heating factors and cooling load. By assigning weights to each factor, this algorithm assesses the significance and impact of various features, effectively filtering out lightweight and less important features. Tables 4 and 5 present the most influential factors and their corresponding weights. Tables 4 and 5 highlight that the overall height factor exerts the greatest influence on the prediction, while the glazing area factor demonstrates the lowest impact.

Table 4. Feature selection for achieving cooling load targets

Attribute	Ranking
Overall height	0.89
Relative compactness	0.63
Wall area	0.42
Glazing area	0.20

Table 5. Feature selection for achieving heating load targets

Attribute	Ranking
Overall height	0.88
Relative compactness	0.62
Wall area	0.45
Glazing area	0.26

4. CONCLUSION

In this paper, machine learning algorithms in the energy sector were examined using energy efficiency datasets. The study was performed in Weka software and the five algorithms, namely linear regression, k-nearest neighbors, decision stump, RBF network, and isotonic regression, available in this software were used. This study's findings demonstrate that algorithms in this field exhibit precision in their predictions and are capable of estimating real-time power consumption and device usage duration. Remarkably, there exist models that can identify the various factors influencing energy consumption in smart buildings and effectively optimize energy usage using these factors. There are also models that can activate communication and sensor technologies in the field of energy and play an important role in optimizing energy consumption by combining renewable energy. In terms of future possibilities, it is recommended to propose algorithms within this field that can forecast the influence of different parameters on energy consumption. Additionally, it is crucial that these algorithms demonstrate the capacity to manage energy usage effectively in extensive IoT networks.

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