The Development of a Real-Time Electricity Calculator System Using Machine Learning to Enhance Energy Efficiency

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Abstract

The development of the electric meter system described in this article is titled as Development of a Real-Time Electricity Calculator System Using Machine Learning to Enhance Energy Efficiency. The primary objective is to improve household energy management through prediction and alerts regarding energy usage. The system is designed to collect electricity usage data and various environmental parameters from households, and it employs five machine learning models to identify the best model for this purpose. The chosen model, Support Vector Regression (SVR), is used to predict energy consumption. In the research methodology, the system records real-time energy usage data into a CSV file. The predictive features include temperature, number of occupants, house size, and appliance usage. This data is standardized before being used to train the SVR model. After training, the model's predictions are evaluated using the Root Mean Square Error (RMSE). The experimental results show that the SVR model effectively predicts electricity consumption, with a normalized RMSE of 57.56 and a cross-validation RMSE of 58.38, indicating the model's accuracy. The visualizations provide a clear understanding of the overall relationship between actual and predicted values. Household electricity usage prediction enables users to plan energy consumption more efficiently, potentially reducing costs and improving energy efficiency. The development of this system can be applied in various fields, including industry and agriculture, to promote energy conservation and reduce environmental impact.

Keywords: real-time electricity calculator system, machine learning, electrical energy consumption, k-Nearest Neighbors model.

1. Introduction

Now, the Provincial Power Authority provides readings from power meters used to collect electricity bills. Periodically, these measurements are obtained to regulate energy use. But occasionally, this might lead to monthly billing that is erroneous, which puts some homes in the uncomfortable position of having to pay more for power than is required. Furthermore, there are instances where homeowners have long periods of absence from home, which allows others to use their electrical meter without authorization. This issue is a common one in several areas [1–3].

Advanced metering infrastructure (AMI) devices, or smart meters, have been developed in recent years by researchers in the domains of electrical, electronic, computer, and allied technical disciplines [4–6]. Modern smart meters can send and record data on energy use in real time, taking the place of mechanical meters. This invention is intended to serve consumers in both the home and the workplace [7],[8]. **Figure 1** provides an outline of their basic functions.

An outline of a smart meter's main functions is given in this operating diagram. Data is first collected by energy sensors and then sent to the processing unit. The data is subsequently managed and kept in memory by the processing unit. Through a communication module, the data is relayed simultaneously to utility providers and a display panel. A power source provides electricity to this circuitry [9–12]. The following characteristics are the focus of the development:

I. Real-time data collection: Smart meters periodically log energy consumption, giving real-time insights into trends in energy usage [13],[14].

II. Two-way communication improves communication between power suppliers and customers by enabling remote meter reading, demand response initiatives, and dynamic pricing models [15].

III. Capability for data analysis: Smart meters can retain extensive data on energy consumption, which allows for sophisticated analysis to optimize energy use and generate customized recommendations [16].

IV. Precise billing: Accurate energy cost computation is ensured by real-time data collection, which reflects actual usage scenarios [17].

V. Better grid monitoring enhances load balancing and outage management by giving power companies real-time grid visibility [18].

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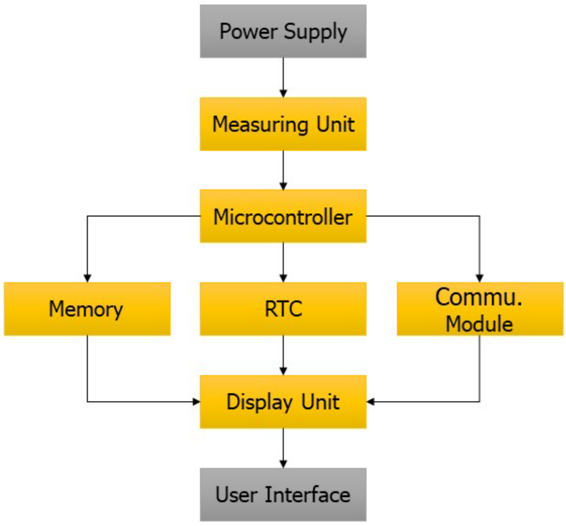

Figure 1 Overview of a smart meter basic.

2. Literature review

2.1 Theories Concerning the Calculation of Electricity Bills

Several equations (Eqs. (1)–(4)) can be used to calculate electricity costs [19], depending on the specifics and goals of the computation. Often utilized formulas consist of:

I. Basic Calculation of Electricity Cost

To figure out how much electricity will cost for a particular appliance or gadget:

$$Cost = Power(kW) \times Time(hours) \times Rate(\frac{baht}{kWh}) \quad (1)$$

where:

- Power is the appliance's power rating expressed in kilowatts (kW).
- Time is the number of hours that the appliance is used.
- The price per kilowatt-hour (baht/kWh) is known as the rate.

II. Calculate the electricity bill.

To get a sense of how much monthly power costs:

$$Monthly\ cost = \sum_{i=1}^{n}(Power_i \times Time_i \times Rate) \quad (2)$$

where:

- n is the number of different applications or devices.
- $Power_i$ is the rating of the i −th appliance in kilowatts (kW).
- $Time_i$ is the amount of time the i −th appliance is used in hours.
- $Rate$ is the cost per kilowatt-hour (baht/kWh).

III. Annual Energy Cost Estimator.

To calculate the cost of power per year:

$$Annual\ cost = \sum_{i=1}^{n}(Power_i \times Daily\ Time_i \times 365 \times Rate) \quad (3)$$

where:

- n is the number of different applications or devices.
- $Power_i$ is the power rating of the i −th appliance in kilowatts (kW).
- $Daily\ Time_i$ is the average daily usage time of the i −th appliance in hours.
- $Rate$ is the cost per kilowatt-hour (baht/kWh).

IV. Calculating power consumption.

To determine an appliance's power consumption:

$$Power(kW) = \frac{Power\ (W)}{1000} \quad (4)$$

where:

- $Power(W)$ is the power rating in watts.
- 1000 is the conversion factor from watts to kilowatts.

2.2 The models using machine learning to calculate electricity bills

A variety of the machine learning methods have been put forth to forecast power costs. Both Bhandarkar [20] and Verma [21] recommend utilizing artificial neural networks, support vector machines, and K-nearest neighbor to forecast power costs and consumption. In contrast, Pereira [22] predicts power usage using an ensemble model that combines support vector machines, artificial neural networks, gradient tree boosting, ridge regression, random forest regression, and severely randomized trees. Atanasovski et al. [23] research analyzes the application of K-NN in forecasting electricity demand in power systems using real data from the Macedonian power system. Experimental results demonstrate the accuracy of the K-NN model in forecasting electricity load.

The application of machine learning methods for predicting power usage has been the subject of numerous studies. K Nearest Neighbors (K-NN) beat other models, obtaining 90.92% accuracy, according to Reddy [24]. Both Aimal [25] and Ashfaq [26] suggested improved versions of K-NN; Aimal combined feature engineering and classification, while Ashfaq used a K-NN and Multi-Layer Perceptron (MLP) combination. To encode causal information, Al-Qahtani [27] presented a multivariate K-NN regression technique that includes binary dummy variables for forecasting UK electricity demand. Together, these experiments demonstrate the potential of K-NN and improved versions for precise prediction of power use.

Recent research explores machine learning applications in energy management and prediction. Shiralkar et al. [28] proposes using decision trees and random forests for energy meter inspection, improving accuracy and efficiency in the power sector. Fan et al.

[29] evaluate various machine learning models for predicting ship energy consumption, finding Random Forest, and Extreme Gradient Boosting most suitable. They note that data preprocessing, normalization, and thermomechanical parameters impact prediction performance. Nooruddin et al. [30] investigate machine learning algorithms for city-scale load forecasting in Kirkuk, Iraq. They compare single and ensemble learning methods, with Bagging demonstrating superior accuracy, particularly for day-ahead forecasts. The study highlights the importance of feature reduction methods and the potential of voting ensemble learning in enhancing forecast accuracy. These studies collectively demonstrate the growing significance of machine learning in energy prediction and management across different sectors.

From a design was determined to utilize an electricity bill calculator and the machine learning model to compare the efficiency of daily and monthly electricity use based on the compilation of relatedresearch described above. This is because of the machine learning model's shown ability to analyze electricity usage effectively.

2.3 Research Concerning the Creation of Systems for Calculating Electricity Bills

This journal has studies about development and application of Internet of Things-based home energy monitoring systems or real-time technology have been the subject of numerous studies as **Table 1**.

Which PZEM-004T module was used by Satriananda [31] and Muhammed [32] to construct real-time energy usage monitoring systems. Satriananda's system shows data on an Android smartphone, while Muhammed's system sends data to the Thing Speak cloud platform. By creating a smart electric meter that can remotely manage household appliances in addition to measuring electricity, Nguyen [33] improved these capabilities even further. By adding a household appliance detection feature, López-Alfaro [34] advanced this and made it possible to gain a more thorough picture of energy usage. All these examples show how IoT-based devices can be used to provide data on energy consumption in real-time and to encourage energy savings.

Two types of sensors are needed as input for the creation and development of tools that calculate electricity costs: AC voltage and current sensors. For this, the PZEM AC Digital Power Meters sensor is employed. This page displays the attributes of each version by compiling the features of all PZEM sensors, as indicated in **Table 1**.

Overview for PZEM-004T or PZEM-005, which are reasonably priced solutions with a basic LCD display but no communication features, are good choices for basic monitoring. They work well for simple voltage, current, and power monitoring. The PZEM-006T, PZEM-007T, PZEM-017, PZEM-035, PZEM-042, PZEM-051, PZEM-061, or PZEM-071 models can provide remote power usage monitoring using a smartphone app due to their Wi-Fi connectivity. This is the best way to monitor energy use and find areas where savings might be made. PZEM-014 or PZEM-016, these meters offer Modbus RTU connection, enabling them to be incorporated into building automation systems and other monitoring platforms, for more sophisticated monitoring and integration. They can handle heavier loads since they have wider voltage and current ranges.

This article chooses the PZEM-016 sensor version from the overview study of all electrical power measurement sensors since it can connect to a Programmable logic controller (PLC) via Modbus RTU and display the findings on a 7-inch HMI screen.

Table 1 Example illustrating the format of a table

Model	Voltage Range	Current Range	Power Range	Communication	Display	Dimensions
PZEM-004T	AC 80-260V	0–100A	0–22kW	None	LCD	79mm × 43mm × 29mm
PZEM-005	AC 80-260V	0–100A	0–22kW	None	LCD	79mm × 43mm × 29mm
PZEM-006T	AC 80-260V	0–100A	0–22kW	WiFi	LCD	79mm × 43 mm × 29mm
PZEM-007T	AC100-240V	0–100A	0–24kW	WiFi	LCD	79mm × 43mm × 29 mm
PZEM-014	AC 80-260V	0–100A	0–22kW	Modbus RTU	LCD	79mm × 85mm × 63mm
PZEM-016	AC 80-400V	0–100A	0–40kW	Modbus RTU	LCD	79mm × 85mm × 63mm
PZEM-017	AC 80-260V	0–100A	0–22kW	WiFi	LCD	88mm × 38mm × 22mm
PZEM-035	AC 80-260V	0–120A	0–30kW	WiFi	LCD	140mm × 90mm × 35mm
PZEM-042	AC 80-260V	0–100A	0–22kW	WiFi	LCD	79mm × 43mm × 29mm

3. Methodology

3.1 The design and development of system

The research was designed based on the current problem as shown in **Figure 2**, this is an install the Modbus communication parameters on the PLC board, such as baud rate, parity, and stop bits, and starting the system are the first steps in the procedure. After that, the PLC board is set up to interact with the PZEM-016 sensor by acting as the Modbus master. To retrieve information from the sensor, a read input command (0X04) is configured. The PZEM-016 sensor receives this read command from the PLC and replies by storing the requested data in the PLC's board specified registers. Next, the raw data is transformed into useful units like amps and volts. The data is validated by the system to make sure it falls within the expected ranges. Subsequently, a gateway device and the PLC board establish a communication link. The gateway uses protocols like MQTT or HTTP/S to send the sensor data to the IIoT cloud. The data is received, saved, and shown on cloud dashboards for both historical trends and real-time analysis as soon as it reaches the cloud platform. This cycle of processes repeats itself, monitoring and uploading data to the cloud continuously. Then we can collect the results of analyzing daily, weekly, and yearly usage to save electricity.

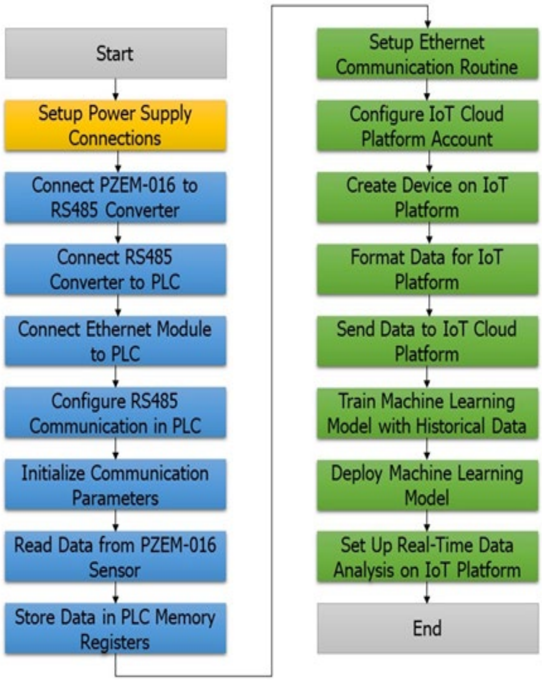

Figure 2 Machine working system flowchart

3.2 Methodology used for processing data from sensor

Base on **Figure 3**, when the input section in this article is the PZEM-016 sensor, it acts as an electrical energy meter, communicating through the RS485 interface to connect to the PLC, which is a processing unit by storing data in dedicated register Then there will be the processing cost of calculating the values that will be displayed as the system can display the results. The display of the system this time can be displayed in 2 formats as follows: 1) Display on the HMI screen for users of the system within the area 2) display on the smartphone screen, which is connected via VNC from the HMI screen, enabling users to check real-time data at any time.

3.3 Methodology used for analysis.

The next section will focus on the capabilities of a processor to collect electricity usage data in the form of daily, monthly, and yearly income. This data can then be used to analyze electricity usage accurately. In this article, a machine learning model is chosen for electricity analysis due to its simplicity. The data collected consists of numerical values represented in the format of electricity bills within the system. Additionally, data on external temperature, day of the week, and time of day, which may affect electricity usage, is also collected. Then, the data is tested using five models: K-NN model, MLP model, SVR model, Ridge Regression, and Linear Regression to find the best model for improved prediction accuracy.

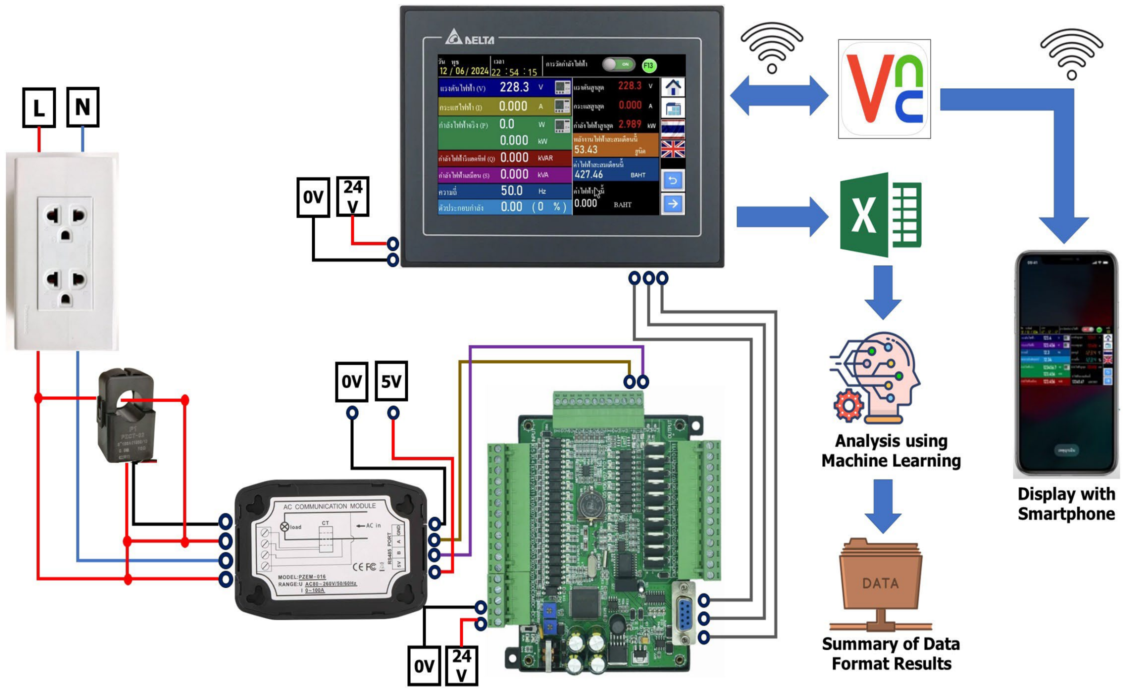

Figure 3 Overview working Electricity Billing System Using Machine Learning

Once the data is collected, the training and testing datasets are set up to evaluate the performance of the appropriate model using various methods. The test dataset is then used to assess the model's performance, including the calculation of various errors, to analyze the results and interpret the factors affecting electricity usage.

The pseudocode in **Figure 4** describes the workflow of a program designed to load data from a

CSV file. The data was collected from electricity usage records to create a dataset. After selecting relevant features and a target variable for prediction, the data is split into training and testing sets, followed by scaling using a Standard Scaler. The code then trains multiple models, including K-NN, MLP, SVR, Ridge Regression, and Linear Regression. Predictions are made on the test data, and the RMSE (Root Mean Square Error) is calculated for each model. Finally, the results are displayed in a graph that compares the actual values with the predicted values, allowing for the evaluation of each model's performance.

```
BEGIN

LOAD CSV file “electricity_bills.csv” into
    DataFrame

SELECT features X from DataFrame
SELECT target y from DataFrame

SPLIT data into training set (X_train, y_train)
    and test set (X_test, y_test)

APPLY StandardScaler to normalize X_train and
    X_test
    FIT scaler on X_train
    TRANSFORM X_train to X_train_scaled
    TRANSFORM X_test to X_test_scaled

FOR each model in [K-NN, MLP, SVR, Ridge
    Regression, Linear Regression]
    INITIALIZE the model
    TRAIN the model using X_train_scaled and
    y_train
    PREDICT     electricity     usage     using
X_test_scaled
    CALCULATE RMSE for the predictions
    STORE the model name and its RMSE

PLOT graphs to compare actual electricity usage
    against predicted usage for each model
    FOR each model
        SCATTER plot of actual vs predicted
values
PLOT  red  dashed  line  indicating  perfect
predictions
        ADD labels and title showing RMSE

DISPLAY the graph

END
```

Figure 4 Pseudocode for machine learning with decision space plotting

4. The Result

4.1 The result of system

The electricity billing machine depicted in **Figure 5** is an automated system designed for monitoring and calculating household electricity consumption, using a Programmable Logic Controller (PLC) as the main processing unit. The device receives data from the PZEM-016 sensor, which measures voltage, current, and energy consumption. Real-time information is displayed on the screen, allowing users to instantly monitor their electricity usage and costs. Control and configuration functions, such as selecting operating modes and setting electricity rates, make the machine adaptable to various household needs. Additionally, it includes a safety feature with an Emergency Stop button, ensuring secure operation. Overall, this machine serves as an efficient and accurate tool for managing and controlling electricity consumption in homes.

Figure 5 Electricity Billing Machine

4.2 Analyze results

In the research titled “The Development of a Real-Time Electricity Calculator System Using Machine Learning to Enhance Energy Efficiency,” the authors collected data from 121 household samples. Each sample includes features such as date, electricity usage, electricity cost, temperature, number of occupants, house size, and appliance usage hours. The data was collected over a four-month period and analyzed to develop a predictive model for electricity usage using machine learning techniques.

For descriptive statistics of the dataset, the authors calculated the mean, standard deviation, minimum, maximum, and median values for each key feature.

These statistics were used to inform the development of the predictive model. To ensure reproducibility of the experiment, the authors applied data normalization techniques to standardize the features before inputting them into the machine learning models. This preprocessing step helps to reduce bias and improve the accuracy of predictions.

The design and development of a real-time electricity bill calculation system is getting a system with functions that can measure voltage, current, frequency, power,

power factor, measure working hours, collect daily electricity usage data, and collect monthly electricity usage data. full model with the working system as shown on figure 3 and the machine design as shown on figure 5.

Figure 6 shows the graph analysis of electrical energy use compared to days of use, while Figure 7 shows electrical energy use compared to temperature. And all of this shows electricity consumption during January - April 2024 and the relationship between electricity consumption and temperature on other days.

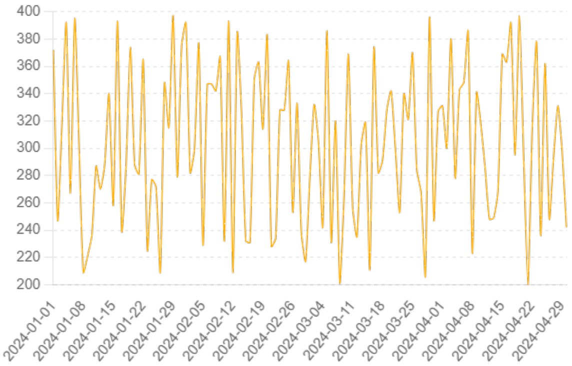

Figure 6 Electricity Usage Over Time

In the research used the dataset named 'electricity_bills.csv' is used to collect data on household electricity consumption. The data was gathered from the PZEM-016 sensor, which measures real-time electricity usage every 10 minutes. The dataset includes key features such as the date ('date'), electricity usage ('electricity_usage'), electricity cost ('electricity_cost'), temperature ('temperature'), number of occupants ('num_occupants'), house size ('house_size'), and appliance usage hours ('appliance_usage').

The data collected from the PZEM-016 sensor includes the amount of electricity consumed during each time interval, which can be analyzed to identify relationships between temperature and electricity consumption, as well as to predict future electricity usage. Examples of other features used for predicting electricity usage include the number of hours appliances are used each day ('appliance_usage'), the density of occupants ('num_occupants'), and the size of the house ('house_size') as shown in **Figure 7**.

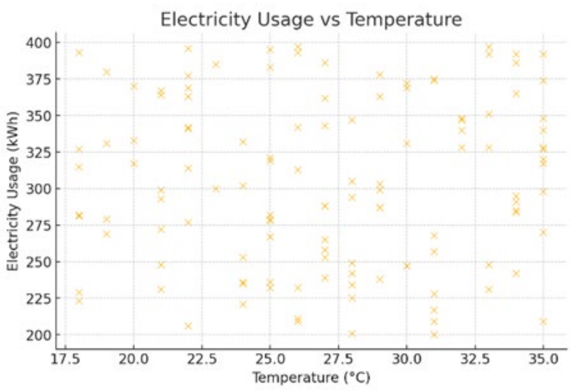

Figure 7 Electricity Usage and Temperature

The electricity Usage and Temperature in Figure is a graph illustrates the relationship between electricity usage (kWh) and temperature (°C). The data points in the graph show a diverse range of electricity usage with no clear linear relationship to temperature. The scattered points indicate that even as the temperature increases or decreases, electricity usage does not consistently follow suit. This variability may be due to other influencing factors, such as the number of occupants or the type of electrical appliances in use. The dispersion of data points suggests that electricity consumption is not solely driven by temperature, but rather by a combination of factors.

When the machine development is complete, from **Figure 5**, Using with 5 models of machine learning technique were selected as follows: the evaluation of prediction performance using models such as K-NN, MLP, SVR, Ridge Regression, and Linear Regression is conducted by calculating the RMSE (Root Mean Square Error). RMSE is a critical metric that measures the discrepancy between the predicted values from the models and the actual values. It is computed by taking the square root of the average of the squared differences between predicted and actual values, providing a quantifiable measure of prediction error. A lower RMSE indicates higher model accuracy. In this research, comparing the RMSE across different models allows researchers to identify the most effective model for predicting electricity usage, thereby contributing to ongoing improvements in household energy management. The RMSE (Root Mean Square Error) was determined as a value used to measure the difference between the predicted values and the observed values with the equation as Eq. 5:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5}$$

When y_i is actual value, $\hat{y}_i$ is predicted value, and n is amount of data which RMSE value as measure of the model's accuracy in predicting the actual value.

As shows in **Figure 8–12** are graphs displayed compare the actual electricity usage with the predicted electricity usage across various models, including K-NN model, MLP model, SVR model, Ridge Regression, and Linear Regression. In each graph, the red line represents the ideal relationship between actual and predicted values, where a well-performing model would have most data, points close to this line. The RMSE (Root Mean Squared Error) shown in each graph indicates the accuracy of the model, with a lower RMSE suggesting a model that predicts more accurately. Among the models compared, SVR model appears to have the lowest RMSE (57.56), indicating the best performance in predicting electricity usage in this scenario.

The next step an applies Time Series Split cross-validation to evaluate the performance of various electricity usage prediction models, including K-NN model, MLP model, SVR model, Ridge Regression, and Linear Regression. The feature data is first normalized using Standard Scaler, then cross-validation is performed using Time Series Split, which splits the data into 5 time-based folds. The RMSE (Root Mean Squared Error) is calculated for each model, and the average RMSE results are stored and displayed in a bar chart to compare the performance across the different models as the **Table 2.**

Table 2. The average RMSE results

Model	RMSE	RMSE
	normalize	cross-validation
K-NN	69.65	66.58
MLP Regression	65.92	73.39
SVR	57.56	58.38
Ridge Regression	60.71	62.59
Linear Regression	60.78	62.94

The results from applying cross-validation on the time-series data indicate that the K-NN model achieved the lowest RMSE at 66.58, signifying that it provides the most accurate electricity usage predictions compared to the other models. In contrast, the MLP model had the highest RMSE at 73.39, indicating greater prediction error. The SVR, Ridge Regression, and Linear Regression models had RMSE values in a similar range, from 58.38 to 60.94. These results demonstrate that cross-validation provides more reliable and standardized performance evaluations for time-series data, with SVR model emerging as the superior model in this case.

5. Conclusion

This article presents the design of a real-time electricity cost calculation system using machine learning to enhance energy efficiency. The study involves analyzing household electricity usage and examining sensors and controllers as shown in Figure 5. The system is designed to support 220-volt electricity usage. Once the devices were fully developed, electricity usage data was collected to determine the effectiveness of the SVR model. The RMSE obtained from the experiments is within an acceptable range, although there might be slight discrepancies. The model demonstrates satisfactory accuracy in predicting actual values. The features used for prediction show a strong correlation with electricity consumption, highlighting the importance of proper feature selection for model accuracy, and indicating potential for further improvement by adding new features or applying different learning techniques.

The SVR model developed in this article effectively predicts the electricity consumption of 220-volt household appliances. The RMSE indicates that the model's accuracy is acceptable. Graphical visualization aids in clearly understanding the relationship between actual and predicted values. The model's accuracy can be improved and enhanced in the future by experimenting with various techniques. Accurate electricity consumption predictions can aid in better energy planning and cost management, benefiting households by saving energy and reducing long-term costs.

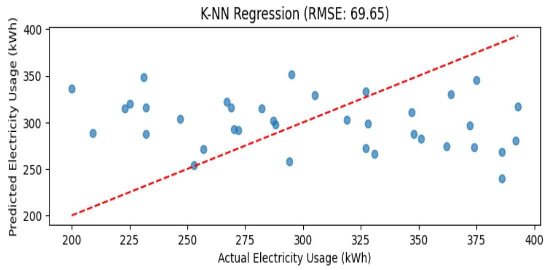

Figure 8 K-NN Regression

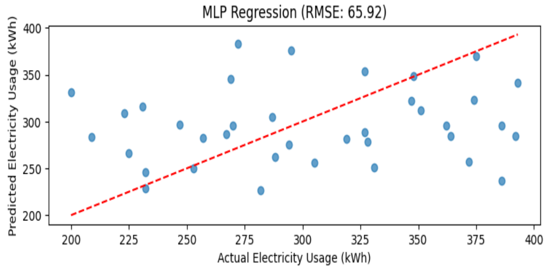

Figure 9 MLP Regression

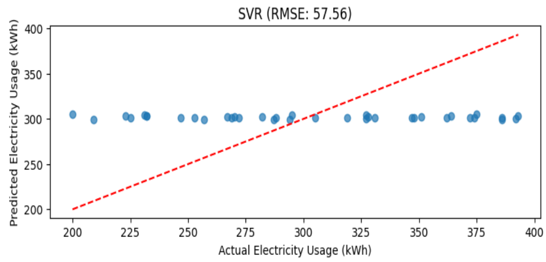

Figure 10 SVR Regression

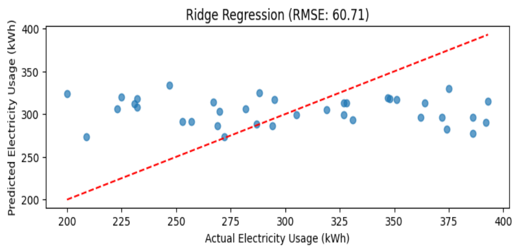

Figure 11 Ridge Regression

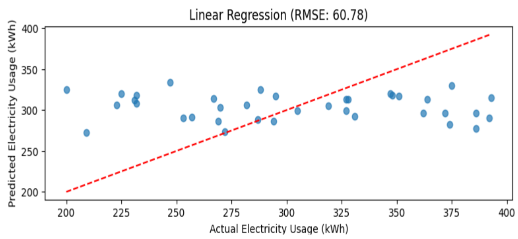

Figure 12 Linear Regression

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