Innovation in Energy Management: Optimizing Electricity Use with the LVQ Perceptron Method

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ABSTRACT

This study proposes an energy management model based on the Learning Vector Quantization (LVQ) Perceptron to improve classification accuracy and support structured decision-making in electricity management. The model classifies customer electricity consumption into three categories: Low, Medium, and High usage. These classifications are then used as recommendations to regulate power plant operations according to actual demand patterns. A hybrid LVQ Perceptron algorithm was developed to select power generation units based on consumption levels. The model performance was evaluated through experiments using different training and testing data compositions, with a constant learning rate of 0.01 and variations in the number of hidden neurons. The results show that increasing the number of hidden neurons improved the classification accuracy. The model achieved 93.7% accuracy with 10 neurons, 93.8% with 20 neurons, and 95.8% with 50 neurons. These findings suggest that the LVQ-based approach is effective in classifying electricity usage data and can serve as an alternative algorithm for optimizing energy distribution. The proposed method contributes to more efficient energy management by aligning electricity generation with consumer demand patterns.

Keywords-energy management; optimization; LVQ Perceptron; accuracy; electricity

I. INTRODUCTION

Java and Bali are the centers of government, industry, and transportation in Indonesia. Java Island has the highest population concentration in Indonesia, with West Java Province having the largest population, reaching 49.9 million people in December 2023, followed by East Java with 41.64 million people and Central Java with 38.13 million people [1]. Overall, Java Island is home to more than half of Indonesia's population, having about 51.8 million households in total. West Java has 16.28 million households and a population of around 48.64 million. East Java has 14.09 million households with approximately 41.14 million people. Central Java has 12.63 million households and a population of about 38.13 million. Therefore, it is not surprising that electricity consumption in Java remains the highest in Indonesia. The percentage of electricity consumption in Java reaches 73.5%, and the installed capacity of electricity continues to grow. In 2021, the installed capacity in Java reached 22,696.94 MW, while the capacity reached 18,890.12 MW. Household electricity consumption in Java has a significant share in total consumption, although household consumption is not as large as industrial consumption; however, due to the larger number of household customers, the contribution is still large.

Fossil-based electricity generation typically requires fuel to power the machines that produce energy [2]. The more electrical energy that is released, the more fuel is needed to drive the engine, as more electrical energy is produced, requiring more fuel to power the engine [3]. For this reason, a digitalization of these plants is needed. Through digitalization, it is possible to monitor and calculate daily production costs. For this reason, it is a key focus of electricity companies in Indonesia to modernize the energy sector. The dependence of fossil fuel-based power plants on fuel leads to increased operational costs as electricity production rises, making electricity use efficiency a major challenge in energy management. This problem highlights the limitations of conventional systems in monitoring consumption patterns and accurately controlling production costs. Therefore, innovation in energy management through digitalization is crucial for optimizing electricity use systematically and data-driven. In this study, the LVQ Perceptron method was applied as an intelligent approach to classify and optimize electricity usage patterns, thereby supporting more efficient and adaptive decision-making in electricity management.

The development of energy digitalization will allow the use of smart technologies such as Machine Learning (ML) and the Internet of Things (IoT) [4, 5]. ML and deep learning algorithms can be applied to power plants to improve monitoring, control, and predictive maintenance, although their implementation is still under active development and research [6]. Such approaches enable better integration among power plants and contribute to improved operational efficiency in Indonesia, with commonly used methods including LVQ, Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), and Support Vector Machine (SVM) [7-9]. LVQ is a supervised classification algorithm that assigns input data to the nearest prototype using distance measures such as Euclidean distance [10]. In the context of energy management, LVQ can be utilized to classify power generation levels, thereby supporting more efficient plant operation, reducing fossil fuel consumption, and lowering production costs at short operational intervals [11, 12].

Most power plants in the Java–Bali region still rely on conventional energy sources, including hydropower and fossil fuels, leading to high electricity production costs and operational inefficiencies. This highlights the need to optimize existing power plants in accordance with ISO 55000 standards through effective energy management based on electricity usage data [13, 14]. Previous studies have utilized smart meter data collected over three years from approximately 2,000 commercial customers, where 15-min interval data were aggregated into monthly consumption values. Functional Principal Component (FPC) analysis revealed that the first principal component captured most of the variability in consumption patterns, whereas additional components (FPC2–FPC4) represented the remaining variations in usage behavior.

The smart system and AC controls were evaluated under five operating conditions and compared with continuous AC operation by analyzing daily electricity consumption after removing outliers based on hourly averages. The optimized control strategy achieved an annual carbon emission reduction of approximately 65% [14]. Electricity consumption data were then classified using LVQ into three energy usage levels: Low (0-6,343 MW), Medium (6,343-16,645 MW), and High (16,645-26,947 MW). The LVQ classification results were converted into binary inputs for the Perceptron algorithm, which determines the activation or deactivation of power plants based on load conditions and plant characteristics. This integrated approach aligns power plant operation with actual demand, improving energy efficiency and reducing fuel consumption.

This study processes secondary electricity consumption data from Java-Bali substations in 2021 to develop an LVQ–Perceptron model for energy management. The dataset consisted of 365 daily data points, which were transformed into 48 vectors with an initial network size of 10 to form three load classes used to propose the operation of three power plants. The LVQ output serves as a data simplification stage to improve the efficiency of Perceptron training in classifying electricity usage for generator activation or deactivation. Positioned within the energy management cluster of smart grid applications, this approach applies LVQ as a supervised competitive learning method and Perceptron as a classification model. Performance evaluation using a confusion matrix shows a precision of 85%, a recall of 82%, and an accuracy of 83%.

LVQ has been applied in various classification tasks, such as identifying eligible recipients of the Family Hope Program (PKH) in Tanjung Lubuk District by classifying household conditions, achieving an accuracy of 94.4% [15]. Similarly, the Perceptron algorithm has been used to assess the eligibility of permanent lecturers, demonstrating a classification accuracy of 98.7% [16]. Although LVQ has been widely utilized across different domains, its application in energy management, particularly for electricity load classification based on historical data with 30-min intervals and production cost estimation, remains limited. LVQ performs classification through competitive learning, while the Perceptron applies a simpler neural network approach, highlighting their complementary roles in classification tasks.

Previous research generally applied LVQ and Perceptron for static classification in contexts separate from energy decision-making, such as determining social aid recipients with 94.4% accuracy or the eligibility of permanent lecturers with 98.7% accuracy. In the Jawa-Bali substation study, LVQ created 3 load classes from 365 annual data points and 48 vectors to simplify Perceptron training with 83% accuracy; however, it was still limited to basic generator activation recommendations. In contrast, other studies emphasized the integration of LVQ Perceptron as an operational optimization tool, directly linking classification results with decisions on electricity usage control, shifting the focus from mere model accuracy toward the effectiveness of load-based energy management. The main difference lies in the research orientation, where previous studies tended to emphasize the accuracy of the classification model, whereas this research stresses the effectiveness of energy management decisions based on the resulting load classes, thereby expanding the role of the LVQ Perceptron from merely a classification tool to an adaptive and applicable energy decision support system. This study aims to develop an energy management model based on ML by integrating LVQ and Perceptron algorithms in classifying electricity consumption patterns in the Java-Bali power system into three load levels: Low, Medium, and High. The classification results are used as the basis for recommendations on activating or deactivating power plants to enhance fuel efficiency and reduce energy production costs. The contribution of this research lies in the application of the hybrid LVQ-Perceptron model for processing 30-min interval electricity consumption data, which is still limited in implementation in Indonesia's electricity sector, as well as serving as a reference for the development of digitalization and energy management systems aligned with ISO 55000 standards.

The novelty of this research lies in the integration of LVQ and Perceptron as a single classification framework for electricity management based on historical data from the Java–Bali substations. This study contributes by demonstrating that LVQ outputs can be effectively utilized as a data simplification stage to enhance the efficiency and performance of Perceptron training in classifying electricity usage patterns. This approach results in a more adaptive operational recommendation system for power plants through the division of three generator operation classes, which has/have been rarely discussed in the last five years, particularly in the context of power classification based on time intervals and optimization of power plant activation decisions. The LVQ-Perceptron integration enriches ML studies in energy management clusters with a more systematic, applicable, and relevant approach for smart grid management.

II. MATERIALS AND METHOD

LVQ–Perceptron is an ML method based on artificial neural networks used for data classification [17, 18]. LVQ works in a supervised manner by grouping data based on proximity to prototype vectors, while the Perceptron functions as a class decision maker through weighting and a linear activation function [19]. The combination of these two algorithms allows for a more efficient and structured classification process, making it suitable for application in energy management systems and operational decision-making. The overall architecture of this integrated approach is illustrated in Figure 1.

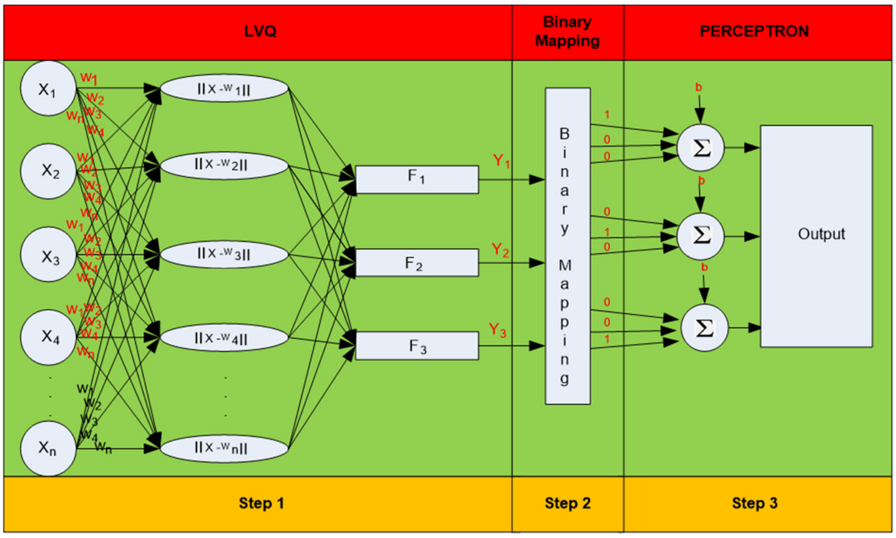


Fig. 1. LVQ Perceptron.

Figure 1 shows the hybrid LVQ–Perceptron model architecture for energy management, which consists of three main stages, namely LVQ, Binary Mapping, and Perceptron. In the first stage, several input variables were processed through the hidden layer using a vector quantization approach to cluster electricity usage patterns. The classification results were then translated into energy parameters (P1, P2, P3) as a representation of power demand levels. In the final stage, these parameters are processed by the Perceptron network through a weighted summation process to produce operational decisions, such as recommendations for turning power plants on or off according to the demand level. Y is the output of LVQ. The formula is:

If $T = C_j$ then:

$$W_{j(t+1)} = W_{j(t)} + \alpha_{(t)}[X_{(t)} - W_{j(t)}] \qquad (1)$$

If $T \neq C_j$ then:

$$W_{j(t+1)} = W_{j(t)} - \alpha_{(t)}[X_{(t)} - W_{j(t)}] \qquad (2)$$

where $W_{j(t)}$ is the weight vector (prototype) of the j-th at iteration or time t, $X_{(t)}$ is the input data vector at iteration t being learned by the LVQ-Perceptron network, T is the actual target label or class of the input data, $\alpha_{(t)}$ is the learning rate at iteration t, which regulates the magnitude of weight changes during the learning process, and C_j is The class represented by the weight vector.

Before discussing the learning process in the proposed model, it is necessary to first understand the basic structure of neurons, which are the main components in the LVQ Perceptron. This structure illustrates how each input variable is processed through weighting and combined to produce a single output. Figure 2 depicts a simple representation of this mechanism in the LVQ Perceptron model.

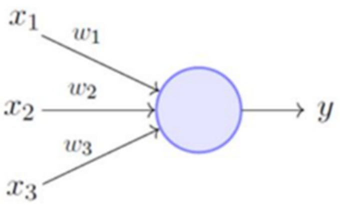


Fig. 2. LVQ Perceptron activation function.

Figure 2 portrays the basic structure of a single Perceptron neuron consisting of three inputs (x_1, x_2, x_3) each with their respective weights (w_1, w_2, w_3). Each input is multiplied by its weight, then summed in the neuron to form a linear combination that is further processed by an activation function to produce a single output (y). This structure illustrates the basic mechanism of the Perceptron in processing inputs into a decision or a single classification result.

The next stage, before applying the weighted function, involves binary mapping to convert the LVQ output values (Y_1, Y_2, Y_3) into binary, as shown in Figure 3, which is employed by the Perceptron to produce outputs that will trigger the switch of the installed device. This process is called weighted summation, as it involves summing the weights and inputs.

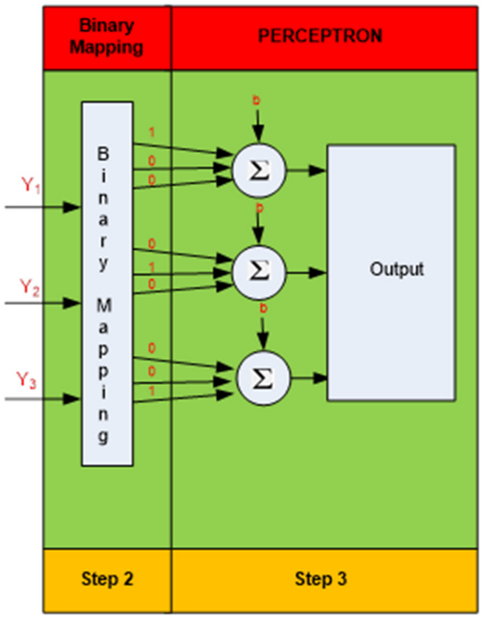


Fig. 3. Binary mapping in Perceptron.

The resulting formula is:

$$Y = \sum_{i=1}^{n}(x_i \cdot w_i) + b \tag{3}$$

where Y is the output of the Perceptron or neuron. Its value is determined by a linear combination of inputs and weights and biases, x_i is the i-th input out of a total of n inputs, w_i is the weight associated with the i-th input. The weight determines how much influence input x_i has on output Y, and b is the bias. The bias is a constant that is added to adjust the output of the Perceptron.

To provide a clear overview of the proposed energy management framework, a comprehensive system architecture is presented to illustrate the flow of data processing from input to final recommendation. The model integrates electricity usage data with the LVQ classification stage and the Perceptron decision layer, forming a structured multi-step process that transforms raw consumption data into actionable energy management recommendations. This visualization clarifies how each component interacts within the system, from data acquisition and pattern classification to monitoring, decision computation, and final recommendation output for each power plant, as presented in Figure 4.

Figure 4 demonstrates the flow of the research method, starting with electricity usage data as the main input. In the initial stage, the data were processed using LVQ to classify consumption patterns based on certain characteristics. The resulting classification is then translated in the next stage into energy demand parameters, which are subsequently processed by a Perceptron network to produce decisions. The final stage consists of energy management recommendations, namely the operational arrangements of power plants, such as Power Plant 1, Power Plant 2, and Power Plant 3, according to the identified demand levels. The following section explains each component presented in the figure in a clear and systematic manner

Step 1: Dataset. This study used secondary data obtained from the Electricity Service Provider (PJL), consisting of electricity usage data recorded every 30 min continuously for 24 h per day, from January 1, 2019, to December 12, 2019, in the regions of Java and Bali. The dataset was validated by an expert in energy management and the former President Director of Indonesia Power until 2023, and it was officially provided for the purposes of this study. The data are limited and not publicly published, but they can be reproduced through collaboration with PJL or by using aggregate electricity load data for comparable periods and time resolutions.

Step 2: The LVQ network classifies the data into three categories: "Low", "Medium", and "High".

Step 3: The output of the LVQ is mapped into binary form: "Low" becomes [1, 0, 0], "Medium" becomes [0, 1, 0], and "High" becomes [0, 0, 1]. These binary outputs are then used as inputs for the Perceptron, which has an output layer with weights set to 1 and biases set to 0.

Step 4: The Perceptron processes this input to generate a signal that determines whether the power plant is turned on or off.

Step 5: The system manages three power plants based on the mapped electricity usage categories: Plant 1, Plant 2, and Plant 3. With the implementation of this system, energy management becomes more efficient and responsive to fluctuations in energy demand, reducing energy waste and improving the operational efficiency of the power plants.

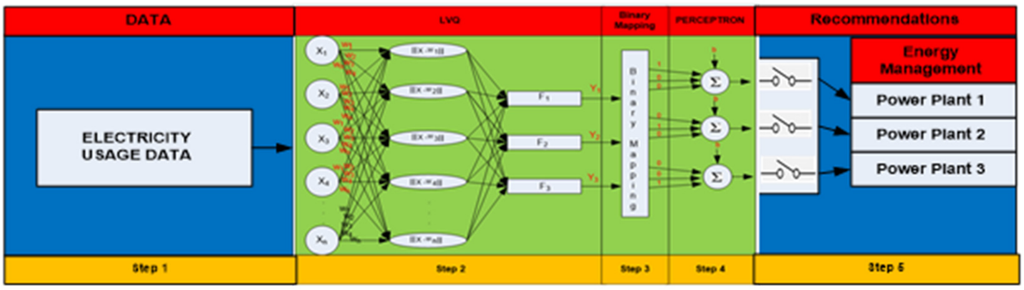


Fig. 4. Research methods.

III. RESULTS AND DISCUSSION

A. Electricity Data

The electricity data represent the patterns of electricity consumption and load in an electrical system obtained from measurements at certain time intervals. These data were used to analyze the characteristics of electricity usage and to support decision-making in the management and operation of power systems efficiently. The dataset used in this study is depicted in Table I.

TABLE I. ELECTRICITY CONSUMPTION DATASET

Date	Hour											
	00:30	***01:00***	***01:30***	***02:00***	***02:30***	**-**	***21:00***	***21:30***	***22:00***	***22:30***	***23:00***	***23:30***	***24:00***
1	12639	12417	12089	12223	12168	-	16213	15593	15142	14879	14529	14356	13953
2	13670	13670	13518	13520	13351	-	16473	15930	15361	15364	14957	14771	14307
3	13968	13925	13828	13653	13531	-	16617	16094	15522	15351	14999	14470	14098
4	14024	13907	13688	13508	13491	-	16220	15776	15325	15313	14936	14502	14409
5	14076	13850	13496	13407	13322	-	16318	15771	15222	15088	14674	14400	14278
6	13932	13635	13494	13272	13269	-	15633	15082	14455	14515	14100	13953	13640
7	13349	13084	12952	12787	12658	-	14866	14360	13882	13860	13593	13335	13013
8	12884	12719	12677	12512	12339	-	16106	15631	15232	15193	14738	14354	14150
9	13866	13759	13688	13562	13319	-	16134	15677	15081	15172	14745	14814	14511
10	13938	13916	13823	13675	13430	-	16434	15795	15208	15220	14805	14527	13958
11	13906	13842	13771	13557	13411	-	16266	15615	15113	15121	14745	14368	14130
12	13754	13682	13447	13304	13194	-	16260	15737	15148	15257	14817	14673	14217
13	14031	13712	13564	13385	13338	-	15725	15174	14574	14612	14213	13845	13627
14	13466	13383	13184	13024	12824	-	15261	14693	14098	14075	13755	13286	13132
15	12793	12759	12579	12378	12307	-	16213	15593	15142	14879	14529	14356	13953
-	-	-	-	-	-	-	-	-	-	-	-	-	-
365	13871	13685	13465	13273	13116	-	15882	15524	14961	15081	14651	14289	14118

Table I shows the electricity usage data for the year 2020, where the rows represent the dates and months, and the data serve as input for LVQ. The data are in MW units, and the columns represent vector data consisting of 48 input neurons, which correspond to the electricity usage recorded every half hour, starting from 00:30 to 24:00. In LVQ, the desired target/class is predetermined, with three target classes (output neurons) for electricity usage: 1. Low, 2. Medium, and 3. High. The data are denoted by $x_1 \ldots x_{365}$ as the input data, while the electricity usage values are assigned as the target/class.

The pre-processing stages include checking data completeness, removing duplicate data, and handling missing values using time-based linear interpolation. Anomalous data resulting from recording errors or extreme fluctuations were identified using statistical limits and adjusted so that they do not significantly affect the load patterns. All data were then reorganized into a consistent time-series format for each day of observation.

Before being processed further, the electricity usage data were normalized to transform the values into a smaller range, making the analysis easier and improving the model performance. Normalization is carried out to ensure that each feature has the same scale, so that no feature dominates the learning process, especially in ML algorithms that are sensitive to scale differences, such as LVQ and Perceptron. In this study, the minimum recorded electricity usage was 6.343 MW and the maximum was 26.947 MW. Normalization was applied using the min–max method so that all values fall within the range of 0–1, while still maintaining the relative pattern of electricity consumption. The distribution of electricity usage data before and after normalization is presented in Figure 5.

Figure 5 illustrates the daily electricity usage pattern, which fluctuates throughout the period from 00:30 to 23:30. In general, electricity consumption tends to be lower in the early hours, then gradually increases in the morning until noon, before peaking in the late afternoon to evening. After the peak period, electricity usage decreases again toward the night. The differences in the curves indicate variations in electricity load between days or data segments, but overall they show a consistent pattern, reflecting the electricity consumption behavior of the community based on daily activities.

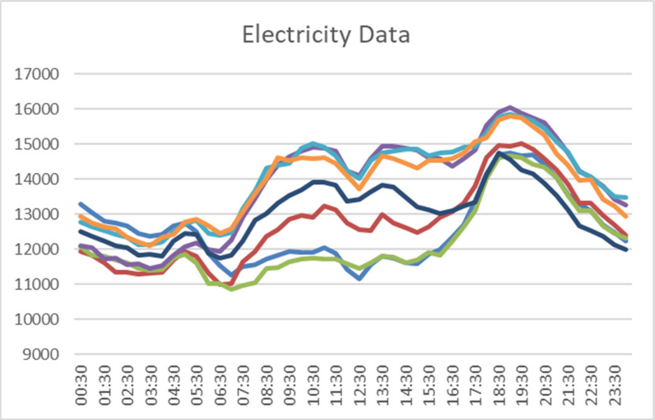


Fig. 5. Electricity data.

B. Learning Vector Quantization

The processing steps in learning/training in the LVQ method can be described through the following LVQ algorithm:

```
Algorithm: LVQ Algorithm
Input: Vector
Output: Weight
Random weight initialization
Set the α (learning rate), maximum number
of epohs, and decrease α
For each epoh until it reaches the maximum
number of epohs:
   Random training data sequence
   For each training data (x, y):
Find the best neurons:
   Calculate the distance between the input
   vector x and each weight vector in the
   layer
   Select the neuron with the closest
   weight to the input (minimum distance)
   Calculate y_pred prediction value using
   the best neurons
        Sum of error: error = y – y_pred
   For each wi weight on the Best neurons:
        Update weight: wi = wi + α * error *
        xi
        Update neighbor weight: wi_neighbor
        =wi_neighbor – α * error * xi
          Update α: α = α – decrease α
   Check the stop criteria (e.g., achieve a
   certain error tolerance or reach the
   maximum number of epohs)
   If the stop criteria are met, exit the
   loop
     If not, move on to the next epoh
```

In addition to the input data, there are predefined target classes for the power settings, which are shown in Table II.

The target class conditions obtained were used to determine the appropriate class for the power required to meet consumption needs.

TABLE II. TARGET CLASSS

Target Class	Description
1	Low power
2	Medium power
3	High power

TABLE III. DATA AND TARGET CLASS

Hour	Day					Class
	X_1	X_2	X_3	-	X_{365}	
00:30	0.3925	0.2733	0.2144	-	0.2971	1
01:00	0.3438	0.2329	0.1582	-	0.2893	1
01:30	0.3324	0.2206	0.1484	-	0.2554	1
02:00	0.2983	0.1833	0.1387	-	0.2565	1
02:30	0.2836	0.1531	0.1121	-	0.2358	1
-	-	-	-	-	-	-
22:00	0.6702	0.7284	0.7568	-	0.6236	3
22:30	0.5924	0.6303	0.6580	-	0.5156	3
23:00	0.5469	0.6308	0.6285	-	0.5211	2
23:30	0.4866	0.5605	0.5678	-	0.4533	1
24:00	0.4567	0.5284	0.4763	-	0.4985	1

After obtaining the data portrayed in Table III, the next step was to normalize them to a range between 0 and 1. The normalization process continued until December 31, 2020, at 24:00. The purpose of data normalization is to enhance model performance. Normalizing the data typically improves the overall model performance, as more homogeneous data help the LVQ algorithm group the data more effectively. The normalization results are listed in Table IV.

TABLE IV. TRAINING DATA

Hour	Day					Class	Average Usage
	X_1	X_2	X_3	-	X_{365}		
00:30	0.3925	0.2733	0.2144	-	0.2971	1	0.2971
01:00	0.3438	0.2329	0.1582	-	0.2893	1	0.2893
01:30	0.3324	0.2206	0.1484	-	0.2554	1	0.2554
02:00	0.2983	0.1833	0,1387	-	0.2565	1	0.2565
02:30	0.2836	0.1531	0.1121	-	0.2358	1	0.2356
-	-	-	-	-	-	-	
22:00	0.6702	0.7284	0.7568	-	0.6236	3	262.50
22:30	0.5924	0.6303	0.6580	-	0.5156	3	243.86
23:00	0.5469	0.6308	0.6285	-	0.5211	2	241.37
23:30	0.4866	0.5605	0.5678	-	0.4533	1	227.52
24:00	0.4567	0.5284	0.4763	-	0.4985	1	217.18

As exhibited in Table IV, the normalized data consisted of one year's worth of electricity usage data, with 365 entries and 48 vectors. After averaging, the training data are selected, which serve as the initial weights for the LVQ. The initial weights must represent the three target classes: Class 1, Class 2, and Class 3.

Table V outlines the classification results for 365 observations across three categories: Class 1, Class 2, and

Class 3. Each row represents an individual data instance, and the values in each column indicate the normalized classification scores produced by the model. The sample data show a general increase in values from Class 1 to Class 3, reflecting a stronger tendency toward the higher class in many observations. For example, both early and final entries display progressively larger scores in Class 3 compared to Class 1 and Class 2. Overall, Table V illustrates how the model differentiates electricity usage patterns by assigning varying levels of class association in a structured manner.

TABLE V. CLASS DATA

No.	Class 1	Class 2	Class 3
1	0.106295	0.1367347	0.4956172
2	0.1925856	0.3825598	0.6450675
3	0.2606598	0.4099229	0.6406492
4	0.2157605	0.2936038	0.6279486
5	0.3407922	0.6248951	0.7740952
-	-	-	-
362	0.380769	0.590211	0.772612
363	0.363058	0.451081	0.746883
364	0.505685	0.758501	0.882412
365	0.525755	0.744484	0.864935

The training data were generated based on the maximum and minimum values derived from the normalized data. The corresponding target data are listed in Table VI, where the representation of target data in binary encoding form for three classes is illustrated. Each class is represented by a one-hot vector, where Class 1 is marked with a value of 1 in the first column, Class 2 in the second column, and Class 3 in the third column, while the other columns are 0. This scheme is used to facilitate the training and evaluation process in neural network-based classification models.

TABLE VI. TARGET DATA

Class 1	Class 2	Class 3
1	0	0
0	1	0
0	0	1

With the number of hidden layers set to 10, the data used consisted of 30% from the Low class, 50% from the Medium class, and 20% from the High class. The learning rate applied was 0.01, as demonstrated in Figure 6.

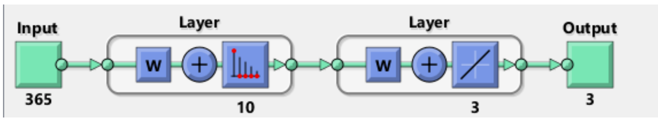


Fig. 6. Learning rate.

Figure 6 displays the feed-forward neural network architecture for classifying electricity usage data, with 365 input units, one hidden layer containing 10 neurons, and the next layer with 3 neurons producing 3 output classes. This structure illustrates the one-way flow of processing from input to classification decision.

The results of the experiment are:

1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 1 1 1 2 2 2 2 2 1 1 2 2 2
2 2 2 2 2 2 3 3 3 3 3 3 3 3
3 3 3 1 1 1

The class distribution is: High Class, with a value of 3, accounts for 23% (11 times), Medium Class, with a value of 2, accounts for 29% (14 times), and Low Class, with a value of 1, accounts for 48% (23 times). Further details are provided in Figure 7.

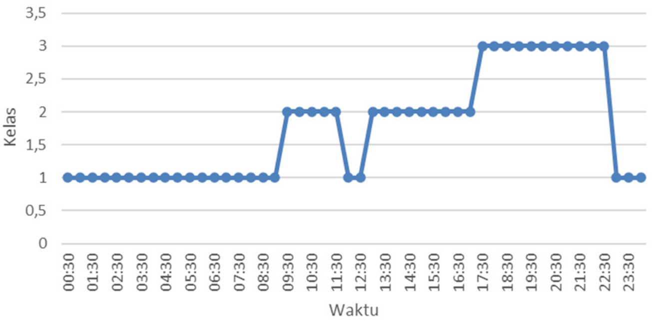


Fig. 7. Class LVQ.

In Figure 7, it can be seen that the highest load occurs between 17:30 and 22:30, with a value of 3. The lowest load is between 00:30 and 09:00, as well as from 23:00 to 24:00, with a value of 1. The medium load is observed between 09:30 and 11:30, and 13:00 and 16:30, with a value of 2.

C. *Network Testing*

Network testing is an important stage in the development of artificial neural network models, aimed at evaluating the network's performance after the training process is completed. At this stage, the trained model is tested using data that have never been used before to measure the network's generalization ability in classification or prediction. The test results were used to assess the model's accuracy, errors, and reliability, allowing an understanding of how well the network can operate optimally and in accordance with the set objectives.

Figure 8 presents the architecture of the Feed-Forward Neural Network used for the classification process. This network has 365 neurons in the input layer representing daily data, followed by a single hidden layer with 10 neurons as the main processing layer. Next, there is an output layer with 3 neurons representing the three classes of the classification results. The processing flow occurs in one direction from input to output through weighting operations and activation functions, which confirms the feed-forward network's characteristic of mapping electricity usage data patterns into predetermined decision classes.

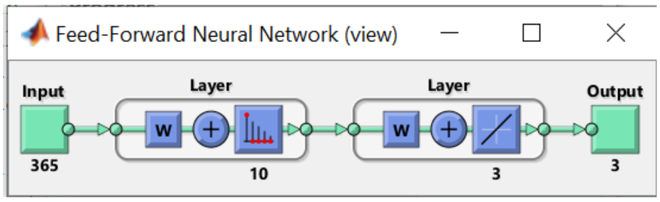


Fig. 8. Network testing.

In Table VII, it can be observed that the network testing is based on test data and training data with proportions of 40% and 60%, respectively. It is evident that varying the number of neurons in the hidden layer, while maintaining a constant learning rate of 0.01, has a significant impact on the model's accuracy. With 10 neurons in the hidden layer, the accuracy achieved was 93.7%. When the number of neurons increased to 20, there was a slight improvement in accuracy to 93.8%. A more substantial increase in accuracy occurred with 50 neurons, reaching 95.8%. However, when the number of neurons increased to 100, 150, 200, and even 500, the accuracy significantly dropped to 71.4%, with no further improvement observed. This suggests that there is an optimal point at 50 neurons in the hidden layer, where any further increase in the number of neurons results in decreased accuracy, indicating that the model has reached or exceeded its optimal capacity.

TABLE VII. NETWORK TESTING WITH DATA

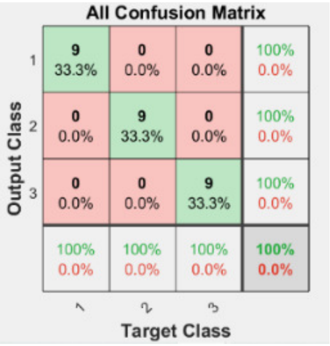
No.	Hidden layer	Learning rate	Accuracy (%)
1	10	0.01	93.7
2	20	0.01	93.8
3	50	0.01	95.8
4	100	0.01	71.4
5	150	0.01	71.4
6	200	0.01	71.4
7	500	0.01	71.4

D. *LVQ Testing Using Confusion Matrix*

In this research, the accuracy level was measured using testing techniques based on the results of power classification with the confusion matrix method. The accuracy in the confusion matrix serves to predict the performance of the system model by measuring the closeness between the actual values and the predicted values. The accuracy calculation used in this study was based on multiclass calculations, which involve more than two classes in the confusion matrix.

1) *LVQ Testing Using Confusion Matrix (60:40 Data)*

LVQ testing using a confusion matrix was conducted to evaluate the model performance in classifying electricity consumption data. At this stage, the data were split with a 60:40 ratio, where 60% of them were used as training data and the remaining 40% as testing data. The confusion matrix was utilized to measure classification performance based on evaluation parameters, such as accuracy, precision, and recall, so that the reliability level of the LVQ model in classifying data into Low, Medium, and High load categories could be determined.



All Confusion Matrix

Output Class \ Target Class	1	2	3	
1	9 33.3%	0 0.0%	0 0.0%	100% 0.0%
2	0 0.0%	9 33.3%	0 0.0%	100% 0.0%
3	0 0.0%	0 0.0%	9 33.3%	100% 0.0%
	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%

Fig. 9. Confusion matrix (60:40).

Figure 9 shows the confusion matrix for the evaluation results of the classification model. This matrix illustrates the model's ability to predict three different classes: Classes 1, 2, and 3, which are represented on the vertical axis as "Output Class" and on the horizontal axis as "Target Class." Each cell in the matrix represents the number of instances predicted by the model for the combination of the correct target class and the predicted output class. The number in each cell indicates the number of correctly or incorrectly classified instances, along with the accuracy percentage for each class. From this matrix, it can be seen that the model:

Successfully predicted 9 data points as Class 1/Low (33.3% of the total), 9 data points as Class 2/Medium (33.3%), and 9 data points as cCass 3/High (33.3%).

There are no misclassified data among these classes, as indicated by the absence of any numbers other than zero in the other cells.

The matrix shows that the model has an even and uniform distribution of predictions among the three classes, with no misclassification occurring. This indicates that the model is able to recognize and classify the data with a high level of accuracy for each class.

2) *LVQ Testing Using Confusion Matrix (70:30 Data)*

LVQ testing using a confusion matrix with a 70:30 data split was conducted to evaluate the performance of the classification model with a larger proportion of training data. A total of 70% of the data were used for the training process, while the remaining 30% were used as testing data. Evaluation using a confusion matrix aims to measure the performance of the LVQ model through accuracy, precision, and recall parameters, allowing for an assessment of the model's ability to classify electricity consumption data into Low, Medium, and High load categories more optimally.

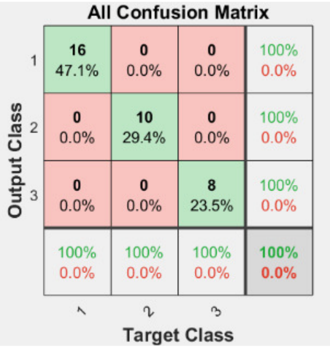


Fig. 10. Confusion matrix (70:30).

Figure 10 displays the confusion matrix which is the result of evaluating the performance of the classification model. This matrix shows how the model classified the test data into three different classes, which are label as 1(Low), 2(Medium), and 3(High) on the vertical (Output Class) and horizontal (Target Class) axes. Each cell in the matrix represents the number of model predictions for the correct combination of class (Target Class) and predicted class (Output Class). The numbers in the cells indicate the number of vectors classified by the model for each of these combinations, along with the percentage accuracy in each class. It can be seen that:

The model correctly predicted 16 vectors as class 1, 10 vectors as class 2, and 8 vectors as class 3, with percentage accuracies of 47.1%, 29.4%, and 23.5%, respectively. No vectors were misclassified, as indicated by the absence of any numbers other than zero in the other cells.

3) *Binary Mapping*

Binary mapping is an important stage in an energy management system that uses LVQ and Perceptron algorithms. After the electricity usage data were processed by the LVQ network, the result is a classification that groups the data into three categories: "Low," "Medium," and "High." To facilitate further processing by the Perceptron, this classification result was mapped into binary form. In this mapping, the category "Low" is represented as [1, 0, 0], "Medium" as [0, 1, 0], and "High" as [0, 0, 1]. Binary mapping is used to connect between LVQ and Perceptron. The program is:

```
def mapping(value):
    if value == "low":
        return [1, 0, 0]
    elseif value == "medium":
        return [0, 1, 0]
    elseif value == "high":
        return [0, 0, 1]
```

The program produces data, as shown in Table VIII.

TABLE VIII. BINARY MAPPING

No.	LVQ	Binary
1	Low	1, 0, 0
2	Medium	0, 1, 0
3	High	0, 0, 1

4) *Perceptron*

The binary mapping converts qualitative information into a numerical format that can be processed by the Perceptron to determine the next action. The Perceptron uses the binary output from LVQ as input. The Perceptron is a simple type of artificial neural network, consisting of one output layer that uses a step function as its activation function to produce the final output. Each binary output from LVQ (Y_1, Y_2, Y_3) is processed by the Perceptron with a weight (w) and bias (b) to produce a signal that will be used for control. It is the Perceptron that will later trigger the switch on the generator side.

Table IX illustrates the classification process performed by a Perceptron based on the input generated by the LVQ model. Each data entry in the table is categorized into one of three classes: "Low", "Medium", or "High", which are then represented as vectors. These vectors are [1, 0, 0] for "Low", [0, 1, 0] for "Medium", and [0, 0, 1] for "High", and are used as input to the Perceptron.

TABLE IX. PERCEPTRON

No	LVQ	Mapping	Input Perceptron	OUT intermediate Perceptron	OUT high Perceptron
1	Low	1, 0, 0	1, 0, 0	ON	OFF
2	Medium	0, 1, 0	0, 1, 0	OFF	ON
3	High	0, 0, 1	0, 0, 1	OFF	OFF

The Perceptron then produces an output indicating the category to which the data belong. If the data are classified as "Low", the Perceptron activates the output for the "Low" category, with the status set to "ON", while the other outputs remain "OFF". A similar process was followed for the "Medium" and "High" categories. This shows the Perceptron's ability to map the input vector to the corresponding output, demonstrating its capacity to recognize and classify data based on the vector representation provided by LVQ.

5) *Energy Management Recommendations*

The output from the Perceptron was used to control three power plants: Plant 1, Plant 2, and Plant 3. The Perceptron's output signal, which is either 0 or 1, determines whether each plant is turned on or off based on the mapped electricity usage categories. This integrated system forms part of the energy management strategy, ensuring efficient and optimal electricity usage. The system enables more responsive energy management by addressing fluctuations in energy demand, reducing waste, and improving the operational efficiency of power plants. The energy mapping model is outlined in Table X.

Perfect classification results should be interpreted with caution, as they are highly dependent on the characteristics of the dataset and do not necessarily indicate generalized model performance. Such results may arise from clear class separation, the use of highly discriminative features, or a relatively small and homogeneous dataset that simplifies the learning process. However, ideal performance can also reflect overfitting or potential data leakage, particularly if data preprocessing is conducted prior to strict separation of the training and testing sets. Therefore, to avoid misinterpretation and ensure the robustness of the findings, additional validation using more rigorous strategies, such as cross-validation and alternative train–test split configurations, is required to assess performance stability and support the reliability of the classification results.

TABLE X. PERCEPTRON

No	Input Perceptron	OUT high Perceptron	OUT intermediate Perceptron	OUT high Perceptron	Generator 1	Generator 2				Generator 3			
					PLTBL	**PLTA**	**PLTUAS**	**PLTGAS**	**PLTG/D**	**PLTUGA**	**PLTG/D**	**PLTUFO**	**PANASBUMI**
1	1,0,0	ON	OFF	OFF	1	0	0	0	0	0	0	0	0
2	0,1,0	OFF	ON	OFF	0	1	1	1	1	0	0	0	0
3	0,0,1	OFF	OFF	ON	0	0	0	0	0	1	1	1	1

E. Discussion

This research contributes to the development of knowledge by showing that hybrid approaches based on classical methods still hold high relevance in the context of modern energy management systems, particularly when the main focus is on efficiency, applicability, and operational reliability. The primary contribution does not lie in creating a new algorithm, but rather in the integration framework that connects pattern classification processes and decision-making into a practical workflow. These findings broaden the perspective that methodological innovation does not always have to take the form of model complexity but can also be achieved through system engineering that is more adaptive to real-world needs. Compared to previous studies, the results of this study show strong alignment with earlier findings that confirm the effectiveness of LVQ and simple neural models in classification tasks based on limited data. However, this research goes further by placing these classification results in an operational context, namely as a direct basis for energy management decision-making. Thus, this study not only confirms the effectiveness of existing methods, but also extends their application scope from mere data analysis to a practical decision support tool.

In terms of alignment with the literature, the findings of this study are consistent with studies that emphasize the importance of balancing accuracy and computational efficiency in real-time systems. The results indicate that increasing model complexity does not always yield significant operational benefits, especially in resource-constrained environments. In this regard, this study reinforces the argument that lightweight and easily interpretable models can be a more sustainable alternative compared to deeper neural architecture-based approaches that are more difficult to implement widely. It is demonstrated that the LVQ–Perceptron combination is capable of providing adequate performance while also meeting the operational requirements of a real-time energy management system. Empirical findings show that the proposed approach is not only effective in terms of technical performance but also excels in stability, decision traceability, and ease of system integration. Thus, the results of this study affirm that the hypothesis regarding the advantage of a simple yet targeted approach in the context of real-world applications is valid and has significant implications for the development of decision support systems in the future.

Although this study shows promising results, there are several limitations that need to be considered. First, the model evaluation was still conducted within a limited data scope and scenarios, so the extent to which the results can be generalized to more diverse operational conditions needs to be further tested. Second, the approach used emphasizes efficiency and simplicity of architecture, so the potential performance improvements that could be achieved from more complex models have not been explored comprehensively. Third, the aspects of real-world implementation in industrial environments are still largely simulated, so practical challenges such as system integration, network latency, and long-term reliability have not been fully addressed. These limitations create opportunities for further research to expand the scope of data, conduct comparative studies with other approaches, and test system performance under actual operational conditions.

IV. CONCLUSIONS

This study used 365 days of electricity usage data with 30-min intervals to classify electricity load patterns using the Learning Vector Quantization (LVQ) method into three classes: Low, Medium, and High. The results showed that the highest load occurred during the 17:30–22:30 time range, with a class value of 3, the lowest load occurred at 00:30–09:00 and 23:00–24:00, with a class value of 1, and the medium load occurred at 09:30–11:30 and 13:00–16:30, with a class value of 2. Testing with a composition of 60% training data and 40% test data showed that the number of neurons in the hidden layer significantly affected model accuracy, with the latter increasing from 93.7% (10 neurons) to 95.8% (50 neurons) at a fixed learning rate of 0.01. These findings confirm that LVQ is effective in classifying electricity usage based on power consumption. The integration of the LVQ classification results with the Perceptron and ESP32 implementation enabled the system to provide operational recommendations related to power plant activation more adaptively according to load requirements. Unlike previous studies, which generally focused solely on classification accuracy, the LVQ-Perceptron approach in this research emphasizes the use of classification results as a basis for energy management decision-making, making it more relevant for power plant operational optimization. The limitation of this study lies in the use of historical data without a predictive component, so comparisons between past and future conditions cannot yet be made.

The practical implications of this approach for real-time energy management systems lie in its ability to provide a fast, stable decision-making mechanism that can be easily integrated into existing infrastructure. With lightweight and computationally efficient architecture, the system can process operational data and generate responses almost instantly, thereby supporting the dynamic energy control needs, such as load adjustment, power distribution management, and response to demand fluctuations. Moreover, the simple model structure enhances reliability and ease of maintenance, as the system can be updated or adapted without requiring significant technical resources. In an operational context, this means that the proposed solution is not only theoretically feasible but also realistic to implement in an industrial environment, particularly in energy management systems that require a balance between response speed, operational stability, and cost efficiency. Further research is proposed to integrate electricity load forecasting, quantitative energy consumption evaluation, and hardware development, so that this method can be more widely applied in regional power grid management, renewable energy generation scheduling, and industrial electricity consumption control with diverse data characteristics.

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