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Electric Energy Measurement System for Energy Management Household with Convolutional Neural Network Method

Devan Hajar Rozali, Rachma Prilian Eviningsih*, Novie Ayub Windarko
Department of Electrical Engineering – Politeknik Elektronika Negeri Surabaya
Surabaya, Indonesia
*rachma@pens.ac.id

Abstract –

Short Term Load Forecasting (STLF) is becoming very important as the use of distributed energy sources, renewable energy, and demand side management increases. Electrical energy is one of the most widely used energy sources, especially in households. To avoid excessive electricity consumption, we propose a household electricity consumption forecasting system using the Convolutional Neural Network (CNN) method. The input of CNN is the power of several household loads measured for one week at 10-minute intervals. This data is used to train the model and predict household electricity consumption for the next week. Forecasting results for a week show a difference in consumption of 3.623 kWh, while with the load management method the difference is 3.439 kWh. With an electricity tariff of Rp1.352/kWh, the estimated electricity cost for the following week is Rp4.892,00, and with load management, the cost drops to about Rp4.649,52 (5% savings). The testing method is done by comparing the forecasting results and actual data for one week. The results show an average difference of only 1.57 W with an average error of 0.07%. This indicates that the CNN model demonstrates strong generalization ability and robustness in handling time-series electricity consumption data. The CNN method is also compared with the Long Short-Term Memory (LSTM) method. As a result, CNN has better performance with CNN RMSE value of 3.688, CNN management of 3.354, while LSTM RMSE of 12.603, and LSTM management of 13.132. Therefore, CNN is proven to be more suitable and accurate for short-term electricity load forecasting in household applications.

Keywords – *CNN; RMSE; STLF; Forecasting; Time Series.*

I. Introduction

THE process of forecasting load for the Short-Term Load Forecasting (STLF) function integrates multiple factors, such as economic trends, cyclical fluctuations, weather conditions, and unforeseen influences [1]. Experts are increasingly relying on advanced techniques, such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM), to forecast the load of Electric Vehicle (EV) charging stations as Artificial Intelligence (AI) technology continues to rapidly progress [2].

The expansion of distributed energy resources contributes to heightened uncertainty within power systems, complicating the precise forecasting of individual energy demands [3]. The utilization of designated power quality analyzers by engineers, electricians, maintenance personnel, and facilities technicians enables them to measure power quality, diagnose electrical systems or equipment, identify energy wastage in buildings (measured in kilowatt-hours, or kWh), and anticipate potential power problems [4].

Energy consumers are pivotal to the functioning of demand response within smart grid systems and can be classified into three distinct categories: residential, commercial, and industrial sectors. The residential sector, in particular, accounts for a substantial portion of the overall energy consumption [5]. In this context, a substantial body of research has focused on the underlying principles and applications of deep learning algorithms to establish accurate and robust models for load forecasting [6].

Convolutional Neural Network (CNN) is one of the methods for image classification. Numerous significant ecological studies utilizing CNN depend on image data, highlighting the necessity of mastering image classification algorithms for advancements in biological research [7]. CNN technology also provides an efficient means for the detection of tumors

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in the brain, particularly within medical image processing that utilizes 3D datasets to illustrate human anatomy [8]. In the context of academic and business applications, CNNs serve as pivotal tools for image segmentation and classification. The application of image recognition is prevalent across various sectors, encompassing automatic image sorting, stock photography, facial recognition, and many other associated activities [9]. Convolutional Neural Networks (CNNs) have emerged as powerful tools for image recognition and classification across various domains [10, 11]. CNNs excel in extracting complex patterns from images, revolutionizing fields such as medical diagnosis, agriculture, and transportation [10]. Their architecture, consisting of convolutional layers, pooling layers, and fully connected layers, enables automatic feature learning and hierarchical representation [12, 13]. CNNs have demonstrated outstanding performance in visual recognition tasks, including image classification, object detection, and semantic segmentation [14]. Applications range from seed classification in agriculture to facial expression analysis for emotion recognition [15, 16]. Recent advancements in CNN research include attention mechanisms, capsule networks, and transfer learning [17]. Despite their success, challenges remain in optimizing CNN models for efficiency and addressing real-world limitations [10, 11].

CNNs also show competitive forecasting accuracy for individual household load prediction [18]. The Long Short-Term Memory (LSTM) network, a distinct type of recurrent neural network, is designed to retain previous data within its memory unit. This feature makes it highly effective for time-series data forecasting, as LSTM can further decrease forecasting error. However, recent studies reveal that existing STLF techniques may not always be sufficient due to unexpected load demand fluctuations [19]. The LSTM layer is essential for recognizing temporal relationships within data, exploiting its ability to utilize prior time steps [20].

Therefore, the capability of the proposed deep learning model is not affected by changes in parameter combinations. The results obtained demonstrate that improved forecasting accuracy is possible through the use of a CNN model that capitalizes on the advantages of various deep learning techniques [21]. These components play a crucial role in electrical equipment management and have established their value in energy management systems [22].

While CNNs are proficient in capturing local trends and detecting repeating patterns across time-series data, they are often insufficient for modeling long-term dependencies. Thus, a hybrid model that combines the strengths of different deep learning architectures may significantly enhance forecasting accuracy [23]. ANN-based methods are widely recognized as dependable, efficient, and comprehensive approaches for tackling complex pattern recognition challenges in power systems, especially with large-scale data [24]. CNN layers are effective in identifying and extracting essential features from time-series data, while also reducing noise and improving overall data quality [25]. Despite these strengths, there is still a gap in practical implementations of CNN-based STLF systems in household settings. This study aims to fill that gap by proposing and evaluating a CNN-based forecasting system using real-time residential load data measured at regular intervals. The findings are expected to contribute to the optimization of energy usage and cost savings in residential energy management.

II. Research Methods

The method used in this research is an experimental method to build a household electricity consumption forecasting system using Convolutional Neural Network (CNN).

i. CNN

This CNN model is one of the most widely used deep learning models in recent years. CNN is essentially a feature extractor that can automatically excavate significant characteristics from input data [26]. The accuracy of forecasting can be enhanced by employing a CNN model that leverages the strengths of different deep learning techniques. CNN is an advanced form of Artificial Neural Network (ANN) that is proficient in processing time-series data using a structured layered network and convolutional operations [27].

The first normalization equation used in this study is shown in Equation (1):

$$\hat{x} = \frac{x - \min}{\max - \min} \tag{1}$$

Here, $\hat{x}$ signifies the standardized value, with max referring to the peak value and min the lowest value in the sample data.

The convolution operation applied in CNN is shown in Equation (2):

$$s(i, j) = (I * K)(i, j) = \sum_m \sum_n I(m, n) K(i - m, j - n) \tag{2}$$

This defines the value at position (i, j) in the convolution result matrix s, derived by placing kernel K over input matrix I and summing element-wise multiplications.

The normalization and denormalization equations are shown respectively in Equations (3) and (4):

$$\text{vars}(:,i) = \frac{\text{data}(:,i) - x.\mu(1,i)}{x.\sigma(1,i)} \tag{3}$$

$$\begin{aligned}\text{vars}(:,i) = \text{stdData}(:,i) \cdot \big(&\max(\text{data}(:,i)) \\ &- \min(\text{data}(:,i))\big) + \min(\text{data}(:,i))\end{aligned} \tag{4}$$

In this study, the CNN model architecture uses 64 feature maps per convolutional layer with kernel size of three time steps. CNN is categorized under supervised learning and is widely used in forecasting and clustering applications in energy management systems [28–30].

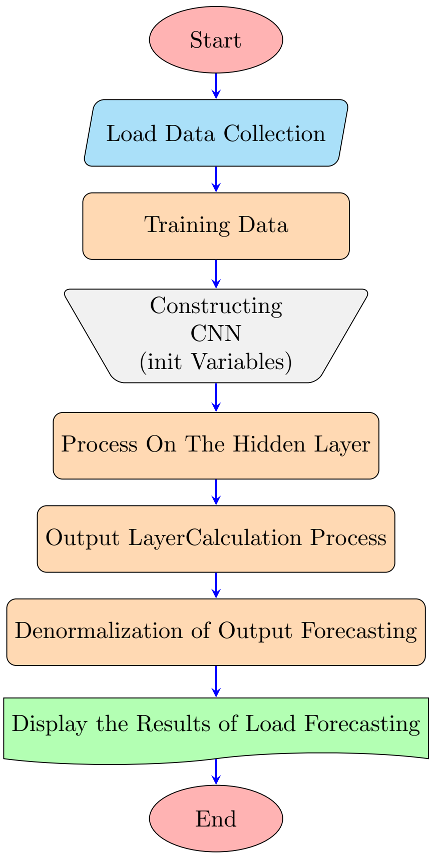

Figure 1: Flowchart of CNN Learning Process [30].

Figure 1 illustrates the learning process of the CNN algorithm used in this research. The process includes the following steps:

1. Data Collection: Real-time household load data collected every 10 minutes.
2. Data Preprocessing: Data divided into training and testing sets, followed by normalization.
3. Model Construction: Initialization of input, hidden, and output layers, filters, kernel size, and activation functions (e.g., ReLU).
4. Training: Multiple convolution and pooling layers used to extract features.
5. Prediction: Dense (fully connected) layers generate outputs.
6. Denormalization: Output values returned to original scale.
7. Visualization: Results displayed in graph or table form.

ii. Data Testing

The forecasting was conducted on real-time household electricity consumption over a one-week period. Load data was collected every 10 minutes and used to train and test the CNN model daily. Table 1 presents the list of load devices and their corresponding testing times.

Table 1: List of Load Devices and Daily Testing Time

Load Device	Watt	Time Testing	Time Management
Lamp	10	17.30–05.00	17.30–04.30
Phone Charger	10	05.00–07.00	04.30–06.00
Laptop Charger	40	07.00–09.00	06.00–07.30
Solder	17	09.00–10.30	07.30–09.00
Fan	20	10.30–05.00	09.00–21.00

Table 1 is used to design the test case for forecasting with flexible model adaptation.

iii. Forecasting Error Analysis

The forecast result is flattened into a vector and decoded through a dense layer to produce output. Forecast accuracy is evaluated using standard error metrics. One commonly used metric is Root Mean Squared Error (RMSE), which computes the square root of the average squared differences between actual and forecasted values. Mean Absolute Percentage Error (MAPE) is another metric that measures error as a percentage of actual values.

These methods are essential to assess how effectively the CNN model predicts real-time household energy consumption patterns.

iv. Energy Management

Energy management involves the systematic review of energy usage aimed at optimizing energy cost based on user demand, financial constraints, and emissions. Controllable and shiftable loads, such as EV charging or appliance usage, can be scheduled to improve demand response effectiveness. This capability forms a core feature of smart energy systems and forecasting plays a critical role in enabling it.

v. Blok Diagram

Figure 2 illustrates the overall system block diagram used in this study.

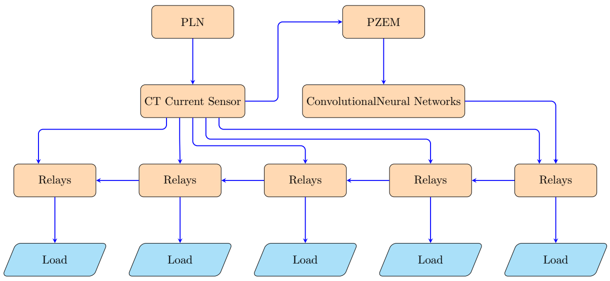

Figure 2: Block diagram of the household load forecasting and management system.

The system begins with the acquisition of measurement data, including current, voltage, and power. These measurements are processed as inputs for the CNN model in the form of power, energy, and time features. Prior to feeding into the model, the input data undergoes normalization, as described earlier in Equation (1) and Equation (3).

The effectiveness of the CNN training process is significantly influenced by the quality and type of input data. In this implementation, the dataset is composed of two types of features: temporal and electrical. Temporal data refers to time-based features, while electrical data includes power and energy readings.

The forecasting output from the CNN model is used to manage loads through an automatic relay mechanism. If predicted loads exceed certain thresholds, the system can disconnect specific appliances to maintain efficiency and avoid overload. This load management process includes four critical components: recording, planning, monitoring, and evaluation.

The system incorporates a PZEM-004T power sensor for precise power measurement, and a Current Transformer (CT) sensor for current measurement. These sensors provide real-time inputs to the forecasting model. CNN serves as the forecasting engine, enabling the system to anticipate consumption trends and make informed load control decisions for residential electrical systems.

III. Results and Discussion

The method used in this research is an experimental method to build a household electricity consumption forecasting system using Convolutional Neural Network (CNN). The stages carried out include several processes, namely designing a data acquisition system, designing a CNN architecture, and building an electricity consumption prediction model.

i. CNN

After we did the training process and collected training data tools, we plotted the regression model between the forecasting and target shown in Figure 3.

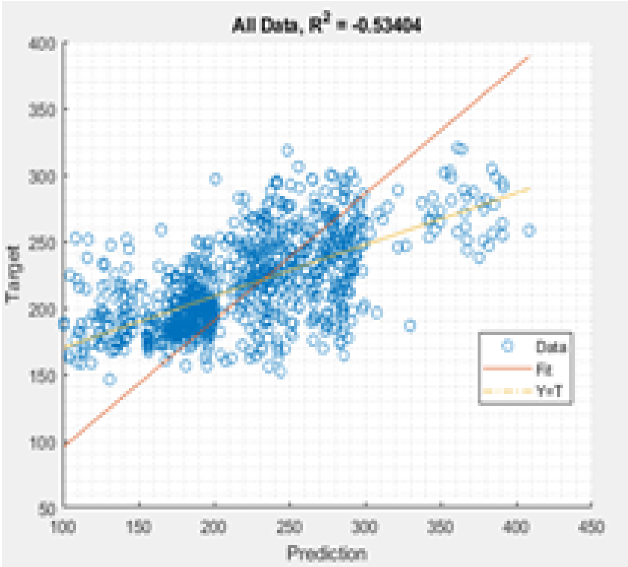

Figure 3: Plot Regresi

The forecasting is the data result from the CNN algorithm and the target data is the result from testing in one week. The result indicates that the CNN algorithm was able to generalize effectively in the training set while providing accurate forecasting in the testing set. It also displays the error distribution associated with the model, derived from both the training and testing sets. A lower error magnitude serves to validate the accuracy of the CNN model.

ii. Forecasting CNN and LSTM

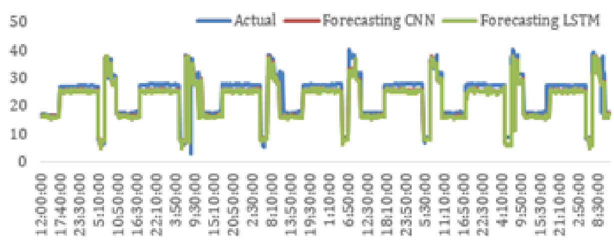

Figure 4: Power Consumption Forecasting CNN and LSTM

In Figure 4, it is shown that the algorithms exhibit commendable performance in accurately forecasting the actual load for the subsequent day. The blue represents the actual data, the orange represents the forecasting data from the CNN, and the gray represents the forecasting results from the processed LSTM results.

Table 2: List of Load Power Forecasting in the First Day (Monday)

Time	Actual (W)	Forecasting CNN (W)	Forecasting LSTM (W)
17:00:00	17	16.66	16.62
17:10:00	17	16.37	16.29
17:20:00	17	16.68	16.60
17:30:00	27.1	26.18	26.08
17:40:00	27.2	25.49	25.44
17:50:00	27	25.85	25.68
18:00:00	27	25.19	25.11
18:10:00	27.1	25.46	25.37
18:20:00	27.1	25.25	25.11
18:30:00	27.1	25.88	25.79
18:40:00	27.2	25.75	25.52
18:50:00	27.2	24.88	24.56
19:00:00	27.2	25.49	25.40

iii. *Forecasting Energy*

Table 3: List of Energy Forecasting CNN in the First Day (Monday), where ε is energy

Time	ε Actual (kWh)	ε Forecasting CNN (kWh)
12:00:00	23.530	27.462
12:10:00	23.533	27.465
12:20:00	23.536	27.468
12:30:00	23.539	27.470
12:40:00	23.542	27.473
12:50:00	23.545	27.462
13:00:00	23.547	27.476
13:10:00	23.550	27.478
13:20:00	23.553	27.481
13:30:00	23.556	27.484
13:40:00	23.559	27.486
13:50:00	23.562	27.489
14:00:00	23.565	27.492

iv. *Forecasting Energy Management*

Table 4: List of Energy Forecasting Management CNN in the First Day (Monday), where ε is energy

Time	ε Actual (kWh)	ε Forecasting CNN (ε kWh)
12:00:00	31.029	34.466
12:10:00	31.032	34.469
12:20:00	31.035	34.471
12:30:00	31.037	34.474
12:40:00	31.040	34.477
12:50:00	31.043	34.483
13:00:00	31.046	34.485
13:10:00	31.048	34.488
13:20:00	31.051	34.491
13:30:00	31.054	34.494
13:40:00	31.057	34.497
13:50:00	31.059	34.501
14:00:00	31.062	34.504

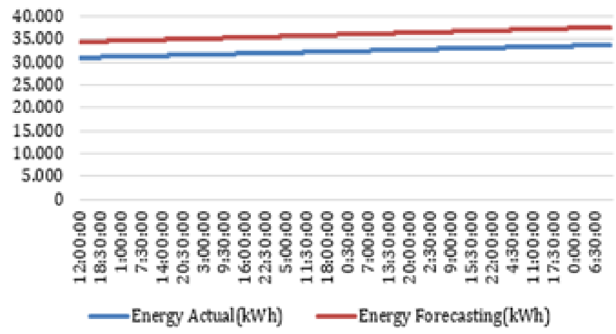

Figure 5: Comparison Actual Energy and Forecasting Management

It can be seen that the tool has successfully obtained power and energy forecasting at home with the same load pattern on campus. It shows that under certain conditions, if the hardware supplies a load with relatively small power, the cumulative energy gain will also be small, and vice versa. On the energy used in 1 week of management, considering a 5% tolerance:

$$3.623 - 5\% = 3.439 \text{ kWh}$$

After obtaining the forecasting value in kWh, the cost to be paid is:

$$\begin{aligned}\text{Energy Forecasting} &- \text{Previous Week's Energy} \\ &= 34.480 - 31.043 = 3.439 \text{ kWh} \\ \text{Total Cost} &= 3.439 \times \text{Rp}1{,}352 = \text{Rp}4{,}649{,}52\end{aligned}$$

v. *Forecasting CNN Accuracy*

Table 5: Forecasting Accuracy of CNN (Monday)

Time	Week 1 Forecasting Power (W)	Week 2 Actual Power (W)	Power Difference (W)	Error %
12:00:00	16.25	17.5	1.25	0.07
12:10:00	16.29	17.2	1.11	0.07
12:20:00	16.19	17.4	1.21	0.07
12:30:00	15.85	17.5	1.65	0.09
12:40:00	15.71	17.4	1.69	0.10
12:50:00	16.13	17.1	1.27	0.07
13:00:00	15.68	17.5	1.82	0.10
13:10:00	15.68	16.9	1.22	0.07
13:20:00	15.90	16.4	0.90	0.05
13:30:00	15.62	16.2	1.28	0.08
13:40:00	15.29	16.2	1.51	0.09
13:50:00	15.29	16.90	1.61	0.10
14:00:00	15.50	16.8	1.46	0.09

After we generate the forecasting model, we implement the model to forecast the consumption of electricity for one week ahead. The results shown in Table 5 on the first day of testing (Monday) indicate that CNN forecasting accuracy works well. The average forecasting error is 1.57 W with an error of 0.07%.

vi. *Root Mean Squared Error (RMSE)*

Figure 7 illustrates that electricity consumption can vary or escalate within a one-week period, as demand for electricity is subject to fluctuations throughout the

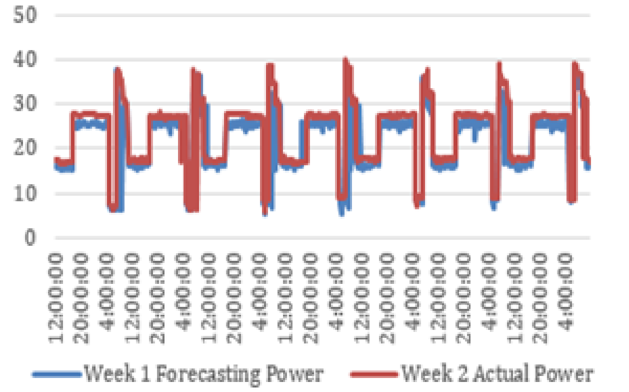

Figure 6: Comparison Week 2 Actual Power and Week 1 Forecasting

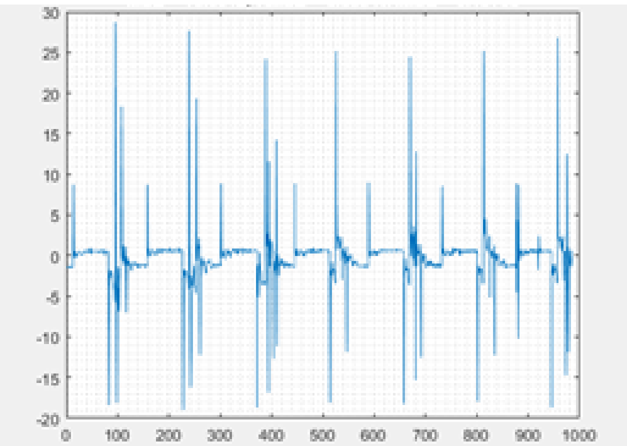

Figure 7: RMSE CNN

day and week. The results obtained from CNN forecasting can be deemed effective, as the actual values closely align with the forecasted values. It is important to account for the difference (error or residuals) between actual and forecasted data, which is evaluated using the RMSE metric.

vii. RMSE CNN Management

The results obtained from CNN forecasting management can be deemed effective, as the actual values closely align with the forecasted figures. It is important to note the difference of value between actual data and forecasted electricity load, commonly referred to as errors or residuals, that usually occur in the forecasting process. For the error analysis we calculate using RMSE as shown in Figure 8.

viii. RMSE LSTM and Comparison

Figure 9 shows the performance of the LSTM model across training and testing sets. However, the model performs with less accuracy than the CNN method. To improve the accuracy, a more effective feature selection

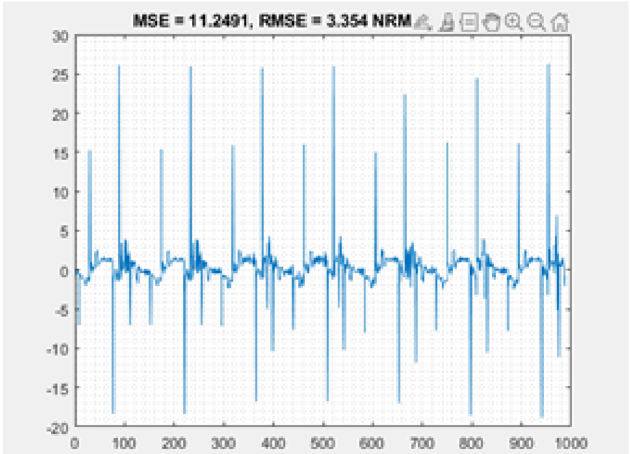

Figure 8: RMSE CNN Management

strategy is recommended, which can be better achieved using the CNN method. Through a systematic iterative process of feature addition and removal, the model can determine the optimal configuration based on the relevance of features to overall model performance.

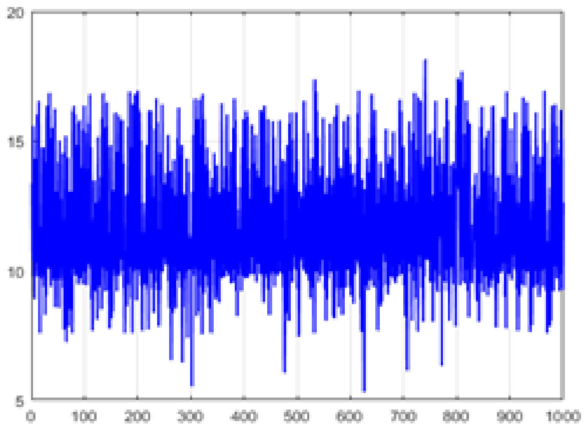

Figure 9: RMSE LSTM

Figure 10 presents an error analysis of the forecasting on LSTM management. The model successfully produced forecasting for both training and test datasets without evidence of underfitting or overfitting. It is noteworthy that the LSTM method applied to the same dataset resulted in an RMSE of 12.603. This method commits most of the errors in the same locations as the CNN method. CNN and LSTM models had RMSE values of 3.688 and 12.603, respectively. CNN Management forecasting achieved 3.354 while LSTM Management resulted in 13.132. The CNN method follows the underlying trends more precisely.

IV. Conclusion

This study used a CNN approach to improve the accuracy of short-term load forecasting in households. The CNN method demonstrated the capability to pro-

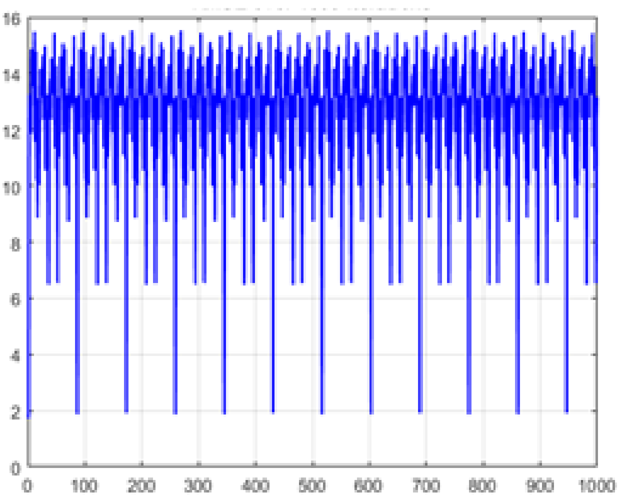

Figure 10: RMSE LSTM Management

Table 6: List of RMSE

Method	RMSE
CNN	3.688
CNN Management	3.354
LSTM	12.603
LSTM Management	13.132

vide accurate and efficient electricity load forecasting by leveraging temporal and spatial patterns in the data. After testing, the CNN forecasting model proved to be acceptably accurate for one-week-ahead forecasting, predicting an energy consumption of 3.623 kWh.

With an electricity tariff of Rp1.352 per kWh for 900 VA household customers in Indonesia, the estimated cost for the following week is Rp4.898,29. Under management constraints with 5% efficiency, the adjusted cost becomes Rp4.649,52.

Based on the conducted tests, the average forecasting error was 1.57 W with an error rate of 0.07%. A comparison of CNN and LSTM showed CNN performed better on the test dataset. RMSE analysis revealed that LSTM had an error of 12.603 (management 13.132), while CNN achieved a lower RMSE of 3.688 (management 3.354), making CNN the more reliable and accurate method.

The CNN approach is therefore more suitable for household electricity forecasting and can also aid in detecting anomalies in power and energy usage, supporting effective daily energy management.

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