



# Prediction of Electricity Usage in The Food and Beverage Department Using Recurrent Neural Network

Lukman Aditya<sup>1</sup>, Wargijono Utomo<sup>2</sup>, Ali Khumaidi<sup>3</sup>, Rahmat Hidayat<sup>4</sup>, Hudzaifah Al Jihad<sup>5</sup>

<sup>1</sup>Electrical Engineering, Faculty of Engineering, Krisnadwipayana University, Indonesia

<sup>2345</sup> Informatics, Faculty of Engineering, Krisnadwipayana University, Indonesia

E-mail: [lukmanaditya@unkris.ac.id](mailto:lukmanaditya@unkris.ac.id)<sup>1</sup>, [alikhumaidi@unkris.ac.id](mailto:alikhumaidi@unkris.ac.id)<sup>3</sup>, [al.ghifari22@gmail.com](mailto:al.ghifari22@gmail.com)<sup>5</sup>

## ARTICLE INFO

## ABSTRACT

### Article history:

Received: September 27, 2021

Revised: October 20, 2021

Accepted: November 25, 2021

### Keywords:

Electricity Usage  
Food and Beverage  
Internet of Things  
Prediction Modelling  
RNN LSTM

The Food and Beverage (F&B) department is one of the sources of income for the company. F&B uses a variety of equipment and machines with large enough power consumption to support operations. F&B can be a disadvantage because of the wasteful use of electrical energy. This research designs and builds an Internet of Things (IoT) prototype that can monitor electricity usage in electrical equipment using sensors then from the data sent by the sensor and additional data predictions are made. The electrical equipment studied included walk-in chillers, blower wheels, exhaust fans, freezers, dishwashers, water heaters and under chillers. To build IoT devices, Arduino nano, AC Current Module, SIM 800L and humidity and temperature sensors are used. Prediction model built using RNN LSTM. IoT devices have succeeded in sending data well after cloud architecture. With 8 neurons in LSTM with lookback has the best performance. The error values for the test data are 51,085 and 18,886 for RMSE and MAE.

Copyright © 2021 Jurnal Mantik.  
All rights reserved.

## 1. Introduction

The Food and Beverage (F&B) Department is a unit that has a function in processing and serving food or beverages to hotel guests, both for coffee shop (restaurant) services, banquets (receptions or meetings), guest rooms, catering, employees, and others. The term F&B is not only used for hotels, food and beverage service providers such as restaurants or cafes often use it [1]. The F&B department is one of the departments that is very profitable for the company but also has a negative side, including the wasteful use of electrical energy, because in the kitchen area there are a number of equipment/machine units with large power consumption of electric watts. In the kitchen area, there are a number of machine tools with relatively large electricity wattage consumption, such as walk-in chiller, blower wheels, exhaust fans, freezers, dishwashers, water heaters and under chillers, as shown in Figure 1. Based on the results of an interview with the F&B manager, Royale Jakarta Golf, that technically equipment with high power does not have to be on continuously but can still support operations as long as it is in accordance with the activities and environmental conditions. Savings can be made by controlling the settings for device requirements such as temperature levels and tool flash times.

The problem of saving electricity in F&B can take advantage of the Internet of Things as a solution to monitor and control the use of electrical energy and to detect abnormalities in equipment and machinery. Monitoring and control systems can assist the engineering department in work activities and identify equipment with energy usage exceeding normal limits. Several methods of predicting the use of electricity have been developed by researchers including the Resident Behavior Learning method [2], Gray Neural Network method [3], probabilistic based method [4], Ensemble Forecasting method [5], deep residual neural network method [6]. ], artificial neural network (ANN) method [7], hybrid method [8], deterministic and probabilistic combined method [9], Deep Learning method [10], Copula Model and Deep Belief Network method [11], DeepBased Conditional Probability method Density Function [12], wavelet method [13], and Hybrid Ensemble Deep Learning method [14].





**Fig. 1.** Electrical Appliances at F&B Department: (a) Water heater, (b) Exhaust Fan, (c) Walk in chiller, (d) Dishwasher, (e) Under chiller, (f) Blower Wheel

Recurrent Neural Networks (RNN) is a form of Artificial Neural Networks (ANN) architecture which is specially designed to process sequential data. RNN is usually used to complete tasks related to time series data [15]. RNN does not just throw away information from the past in its learning process. This is what distinguishes RNN from ordinary ANN. RNN is able to store memory / memory (feedback loop) which allows it to recognize data patterns well, then use them to make accurate predictions. The way that RNN can store information from the past is by looping its architecture, which automatically keeps information from the past stored. The purpose of the research is to design and build a prototype that can monitor the use of electricity in the equipment then predictions are made from the data sent by the sensor. Prediction model built using RNN LSTM. The resulting prediction model can be used as a recommendation to regulate electrical equipment in order to reduce the cost of using electricity.

## 2. Method

The research implementation method can be seen in Figure 2. The first stage is problem identification by conducting observations and interviews at the F&B department, obtaining some data on electrical equipment, processes and equipment settings to support work operations. The second stage is designing and assembling Internet of Things (IoT) devices, followed by the third stage, which is designing cloud server architecture [16]. The fourth stage is to build a prediction model using the RNN LSTM to get the use of the electrical load, followed by the fifth stage, which is to evaluate the model. LSTM is one type of Recurrent Neural Network (RNN) where modifications are made to the RNN by adding a memory cell that can store information for a long period of time [17]. LSTM is proposed as a solution to overcome the vanishing

gradient in RNN when processing long sequential data. This vanishing gradient problem causes the RNN to fail to capture long term dependencies [18], thereby reducing the accuracy of a prediction on the RNN [19]. Figure 3 illustrates the architecture of the LSTM. In LSTM there are 3 gates namely input gate, forget gate and output gate.

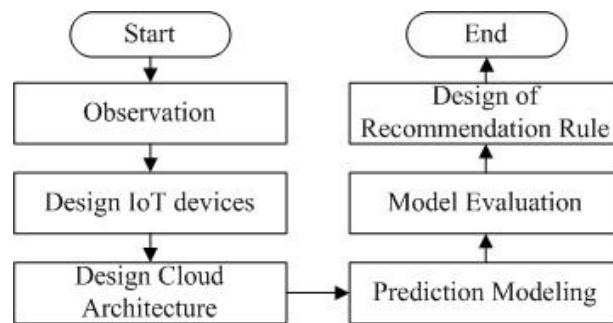


Fig. 2. Research Stages

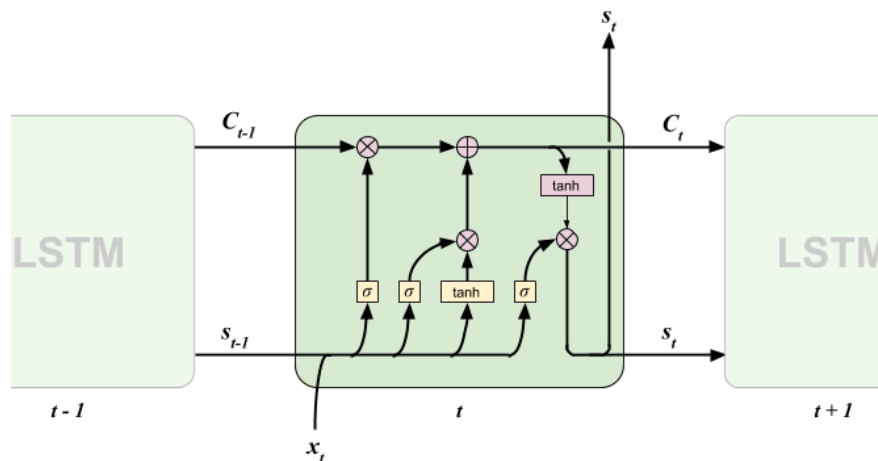


Fig. 3. Architecture of RNN LSTM

In the development of the model, the stages carried out are Description of the Dataset from the data sent by the sensor combined with data from the manager. The attributes that make up the dataset include data on equipment electrical power usage, temperature, humidity, operational activities, data from air stations including air pressure, humidity, and temperature. Then a correlation analysis is carried out, to obtain the right model, the calculation of the correlation coefficient between the attributes that compose the dataset is important to do, especially when these attributes are available in large quantities. It is possible that not all of these attributes are relevant for predicting a target. The next stage is the selection of input features and predictor models using the recursive feature elimination (REF) method to rank various attributes that will be used as input predictor models. The LSTM used as a predictor model in this study uses the root mean squared error (RMSE) and mean average error (MAE), as evaluation parameters.

### 3. Result and Analysis

Figure 4 shows the results of the device design and has been built using Arduino nano components, AC Current Module, SIM 800L and humidity and temperature sensors. The IoT devices will be installed on electrical equipment. The device will send data according to the cloud architecture built in Figure 5. Table 1 is the dataset attribute used in the development of the prediction model.

Each input group will be trained, and then it is determined which input group gives the best results. As an initial selection, LSTM with a number of 8 neurons is assigned to all input groups, and the lookback of input data to the model is set to 1. The lookback indicates the length of the data that will be used to predict the next condition. Lookback 1 means that one piece of data is currently used to predict one piece of data in the future. Another example, if the lookback is set with a value of 4, then 4 data are used to predict one data

in the future. Because each data is taken at 10 minute intervals, this scenario means that the current 10 minutes are used to predict the next 10 minutes. To get a better insight, the experiment was conducted three times for each category, and the best results were selected from each category.

**TABLE 1**  
ATRIBUT DATASET

Attribute	Unit	Description	Attribute	Unit	Description
Date	dd:mm:yy hh:mm:ss	Date Time	OpHour	dd:mm:yy hh:mm:ss	Operasion Hour
App	Unit	Appliances	RH2	%	Environment humidity
EP	Wh	Energy use total	PressArea	mmHg	Area Pressure
T1	°C	Equipment temperature	TArea	°C	Area temperature
RH1	%	Equipment humidity	RHArea	%	Area humidity
T2	°C	Environment temperature	SetApp		Appliances normal settings

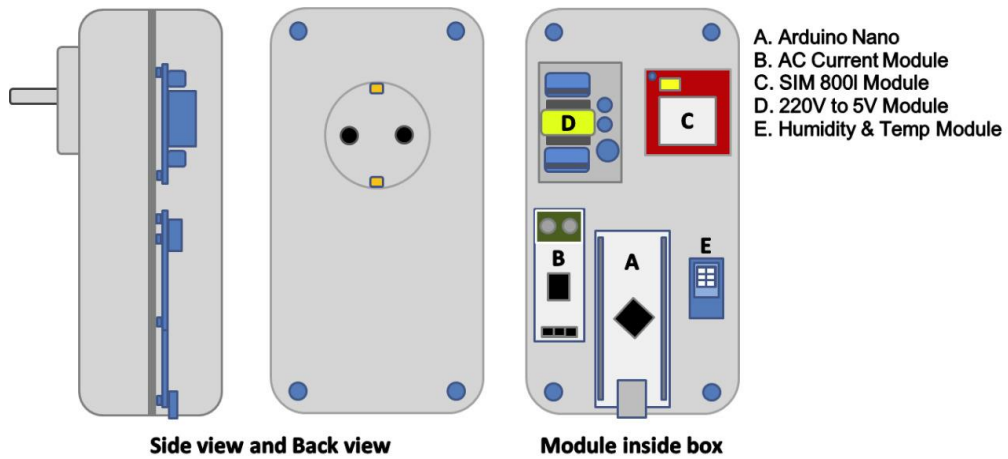


Fig. 4. Design of IoT devices installed on electrical equipment

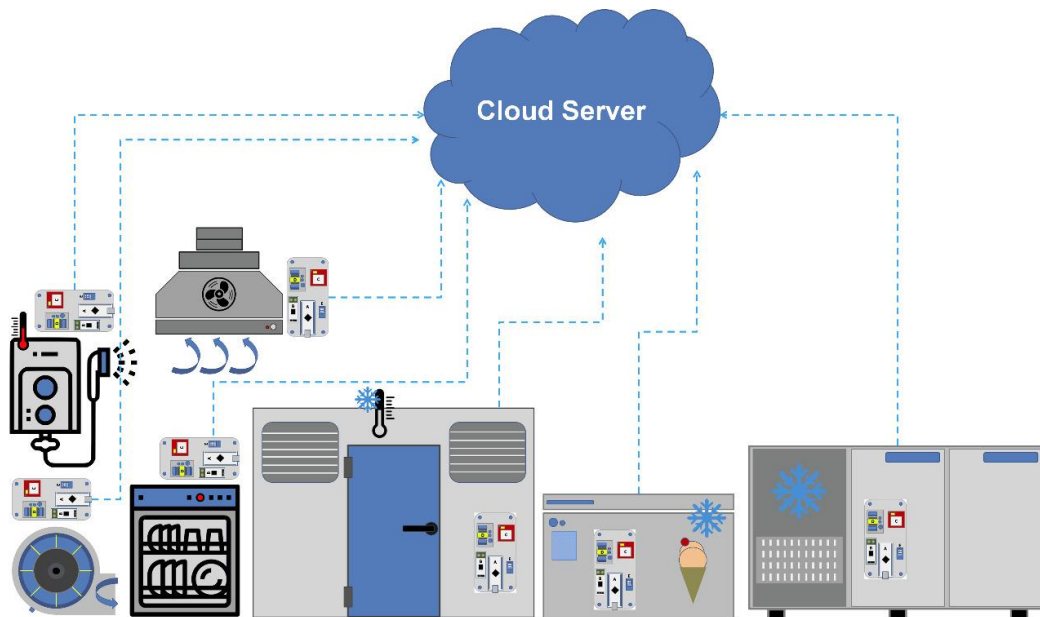


Fig. 4. Cloud Architecture

**TABLE 2**  
RESULTS OF COMPARISON OF THE NEURONS NUMBER

Neuron Number	RMSE	MAE
8	51.085	18.886
32	53.431	27.842
64	53.183	27.559
128	54.048	30.907

One of the most regulated hyperparameters in modeling using LSTM is setting the number of neurons. In this study, neurons will be combined with a certain number, and the final results obtained are observed. Each stage will be repeated three times, and the best results are shown in Table 2.

Based on the experimental results, it is found that increasing the number of neurons will not necessarily improve the performance of the model. It can be seen that the number of neurons as many as 8 still produces smaller error values, which are 51,085 and 18,886 for RMSE and MAE, respectively. The small number of neurons has its own benefits. In terms of file size, the smaller the number of neurons, the smaller the file size and the complexity of the calculations that the model has to do. This is certainly very advantageous, especially if the model has to be run on machines that have limited resources.

#### 4. Conclusion

Internet of Things devices have been successfully built and deliver data well after cloud architecture. The application of the LSTM RNN to predict the amount of electrical energy use from an equipment by using the type of attributes used and the architecture of the predictor model. With 8 neurons in LSTM with lookback has the best performance. The error values for the test data are 51,085 and 18,886 for RMSE and MAE.

#### 5. References

- [1] A. Khumaidi, "Sistem Monitoring dan Kontrol Berbasis Internet of Things untuk Penghematan Listrik pada Food and Beverage," *J. Ilm. Merpati*, vol. 8, no. 3, pp. 168–176, 2020.
- [2] W. Kong, Z. Y. Dong, D. J. Hill, F. Luo, and Y. Xu, "Short-Term Residential Load Forecasting Based on Resident Behaviour Learning," *IEEE Trans. Power Syst.*, vol. 33, no. 1, pp. 1087–1088, Jan. 2018, doi: 10.1109/TPWRS.2017.2688178.
- [3] B. Li, J. Zhang, Y. He, and Y. Wang, "Short-Term Load-Forecasting Method Based on Wavelet Decomposition With Second-Order Gray Neural Network Model Combined With ADF Test," *IEEE Access*, vol. 5, pp. 16324–16331, 2017, doi: 10.1109/ACCESS.2017.2738029.
- [4] Y. Wang, Q. Chen, N. Zhang, and Y. Wang, "Conditional Residual Modeling for Probabilistic Load Forecasting," *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 7327–7330, Nov. 2018, doi: 10.1109/TPWRS.2018.2868167.
- [5] Y. Wang, Q. Chen, M. Sun, C. Kang, and Q. Xia, "An Ensemble Forecasting Method for the Aggregated Load With Subprofiles," *IEEE Trans. Smart Grid*, vol. 9, no. 4, pp. 3906–3908, Jul. 2018, doi: 10.1109/TSG.2018.2807985.
- [6] K. Chen, K. Chen, Q. Wang, Z. He, J. Hu, and J. He, "Short-Term Load Forecasting With Deep Residual Networks," *IEEE Trans. Smart Grid*, vol. 10, no. 4, pp. 3943–3952, Jul. 2019, doi: 10.1109/TSG.2018.2844307.
- [7] W. Kong, Z. Y. Dong, Y. Jia, D. J. Hill, Y. Xu, and Y. Zhang, "Short-Term Residential Load Forecasting Based on LSTM Recurrent Neural Network," *IEEE Trans. Smart Grid*, vol. 10, no. 1, pp. 841–851, Jan. 2019, doi: 10.1109/TSG.2017.2753802.
- [8] K. Park, S. Yoon, and E. Hwang, "Hybrid Load Forecasting for Mixed-Use Complex Based on the Characteristic Load Decomposition by Pilot Signals," *IEEE Access*, vol. 7, pp. 12297–12306, 2019, doi: 10.1109/ACCESS.2019.2892475.
- [9] C. Feng, M. Sun, and J. Zhang, "Reinforced Deterministic and Probabilistic Load Forecasting via \$Q\$-Learning Dynamic Model Selection," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1377–1386, Mar. 2020, doi: 10.1109/TSG.2019.2937338.
- [10] Y. Hong, Y. Zhou, Q. Li, W. Xu, and X. Zheng, "A Deep Learning Method for Short-Term Residential Load Forecasting in Smart Grid," *IEEE Access*, vol. 8, pp. 55785–55797, 2020, doi: 10.1109/ACCESS.2020.2981817.
- [11] T. Ouyang, Y. He, H. Li, Z. Sun, and S. Baek, "Modeling and Forecasting Short-Term Power Load With Copula Model and Deep Belief Network," *IEEE Trans. Emerg. Top. Comput. Intell.*, vol. 3, no. 2, pp. 127–136, Apr. 2019, doi: 10.1109/TETCI.2018.2880511.
- [12] M. Afrasiabi, M. Mohammadi, M. Rastegar, L. Stankovic, S. Afrasiabi, and M. Khazaei, "Deep-Based Conditional Probability Density Function Forecasting of Residential Loads," *IEEE Trans. Smart Grid*, vol. 11, no. 4, pp. 3646–3657, Jul. 2020, doi: 10.1109/TSG.2020.2972513.



- [13] L. Alfieri and P. De Falco, "Wavelet-Based Decompositions in Probabilistic Load Forecasting," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1367–1376, Mar. 2020, doi: 10.1109/TSG.2019.2937072.
- [14] Z. Cao, C. Wan, Z. Zhang, F. Li, and Y. Song, "Hybrid Ensemble Deep Learning for Deterministic and Probabilistic Low-Voltage Load Forecasting," *IEEE Trans. Power Syst.*, vol. 35, no. 3, pp. 1881–1897, May 2020, doi: 10.1109/TPWRS.2019.2946701.
- [15] A. Sherstinsky, "Fundamentals of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) network," *Phys. D Nonlinear Phenom.*, vol. 404, p. 132306, Mar. 2020, doi: 10.1016/j.physd.2019.132306.
- [16] N. Hikmah and A. Khumaidi, "Rancang Bangun Prototipe Pengusir Hama Burung Menggunakan Sensor Gerak RCWL Microwave Berbasis Internet of Things," *Simetris J. Tek. Mesin, Elektro dan Ilmu Komput.*, vol. 11, no. 2, pp. 560–567, Oct. 2021, doi: 10.24176/simet.v11i2.5071.
- [17] A. Khumaidi, R. Raafi'udin, and I. P. Solihin, "Pengujian Algoritma Long Short Term Memory untuk Prediksi Kualitas Udara dan Suhu Kota Bandung," *Telematika*, vol. 15, no. 1, pp. 13–18, 2020.
- [18] A. Saxena, T. Sukumar, and T. Nadu, "Predicting bitcoin price using LSTM and Compare its predictability with Arima model," *Int. J. Pure Appl. Math.*, vol. 119, no. 17, pp. 2591–2600, 2020, doi: 10.13140/RG.2.2.15847.57766.
- [19] Z. Zhao, W. Chen, X. Wu, P. C. Y. Chen, and J. Liu, "LSTM network: a deep learning approach for short-term traffic forecast," *IET Intell. Transp. Syst.*, vol. 11, no. 2, pp. 68–75, Mar. 2017, doi: 10.1049/iet-its.2016.0208.