International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Online Fuzzy Logic Prediction of Electrical Load Based on Real-Time Measurements During the Covid-19 Pandemic

Dikpride Despa [1,2], Gigih Forda Nama [2,3,4], Trisya Septiana [2,3], Meizano Ardhi Muhammad [3]

Submitted: 20/01/2023 **Accepted:** 25/03/2023

Abstract: As technologies advance and the population grows, electrical energy became one of the necessities for many peoples. Because the availability of electrical energy is limited, it requires various ways to be used efficiently. Electrical load monitoring usage in Indonesia still require an electrical officer to come to an electric panel location to record electrical usage. During the COVID-19 pandemic, it is not feasible to locally visit an electric panel because of the many restrictions. Remote monitoring using Internet of Things (IoT) can be used to address the problem. Going further, by knowing the electrical load usage, prediction can be done using fuzzy logic as a way to understand how to use electricity efficiently. Thus, a fuzzy logic load forecasting system IoT is developed in this research. Fuzzy variables used in this system are time of day, days of the week, measured loads, and forecasted loads. The research produced a system that predicts electrical load with one hour of accuracy based on the previous week's data. The average prediction error rate of the system is 9.48%. The implemented system is available on a web server and can be accessed via a web browser, either via a computer or cellphone. The system allows users to monitor and predict electrical load usage regardless of time and place.

Keywords*: forecasting, fuzzy logic, online, electrical load, IoT, electricity*

1. Introduction

The growth of electricity has been the driving force for the modern way of living. It has been one of the most important sustenance in the technological era. It is of utmost importance to use the power in the right way. It can only be done if the electric load in the system can be monitored.

In Indonesia, load monitoring is done manually by visiting and recording the measurement on-site. Load measuring is done manually through an electric panel for amperage, voltage, and even wattage. This kind of system is really bothersome and even cumbersome during the COVID-19 (coronavirus disease of 2019) pandemic. each electric panel needs to be visited on-site one at a time and this is not feasible during the COVID-19 pandemic. The COVID-19 pandemic has made it is hard for an electrical officer to visit the consumer electric panel to read the monthly electricity load usage. There is a chance for the electrical officer to be infected with COVID-19 along the way. Up to now, the State Electricity Company bills consumers based on last month's electricity consumption which sometimes has a difference due to manual recording.

Internet of Things (IoT) opens the possibility to measure electric amperage, voltage, and even wattage automatically, online, and in real-time through the internet. Research on online electrical monitoring systems has been done in work [2][3]. In preliminary research 2, the sensor must be installed in series with the power line before the load. Research 3 did not place the current sensor in series but it uses a clamp current sensor. Research 3 used two controllers: Arduino and Raspberry Pi. Arduino is used to processing data from sensors and sent it to Raspberry Pi. Raspberry Pi is used to process data and represent it in a meaningful format through a web server.

Electrical load forecasting is a way to predict future load using past measured variables [4][5]. Electrical load forecasting research has been done in many ways. Linear regression-based forecasting has been done in research [1]. This type of forecasting is used to project the Lampung power needs in the future 1. Another electrical load forecasting using neural network is done in [6] with an accuracy of 99.12%. Fuzzy based system also has been done in [7]. The fuzzy system predicts with 12.14% error 7. All of these researches were done in a small window period.

Fuzzy based forecasting approach [8] powered by IoT is designed and realized in this research. IoT is experiencing rapid growth in interfacing machines and devices to the internet, and eventually to users. The aim is, with the help of IoT, to provide meaningful information that will allow the user to understand and act accordingly [9]. Forecasting is approached using fuzzy logic. Fuzzy logic uses a combination of mathematical predictive power and human subjectivity to create the best model possible. Human subjectivity allows rules to be applied in the prediction.

[1] *Department of Electrical Engineering, University of Lampung*
[2] *Department of Professional Engineering Program, University of Lampung*
[3] *Department of Informatics, University of Lampung*
[4] *Doctoral Program in Environmental Science, University of Lampung*
Corresponding Email: gigih@eng.unila.ac.id

The implemented system is provided on a web server and can be accessed via a web browser [10], either via a computer or cellphone. The system allows users to monitor and predict electrical load usage regardless of time and place. And, for the electrical officer, an easier way to know the electrical load measurements. Fuzzy-based forecasting is a type of forecasting approach that uses fuzzy logic to analyze and predict future trends. Fuzzy logic is a mathematical framework that allows for the representation of uncertain and vague information. In fuzzy-based forecasting, historical data is analyzed using fuzzy logic to create a model that can predict future trends. The fuzzy-based forecasting approach involves the following steps:

- Data collection: Historical data is collected on the variable of interest, such as sales, demand, or stock prices.
- Fuzzyfication: The data is then transformed into fuzzy sets using linguistic variables, such as "low," "medium," and "high," to represent the different levels of the variable.
- Rule creation: Fuzzy rules are then created using if-then statements based on expert knowledge or historical data. For example, "if the demand is high and the price is low, then the sales will increase."
- Inference: The fuzzy rules are used to make predictions about the future trend of the variable. The rules are applied to new data, and the degree of membership of each fuzzy set is calculated.
- Defuzzyfication: Finally, the fuzzy output is transformed back into a crisp value using a defuzzyfication method such as centroid, mean-max, or height methods.

Fuzzy-based forecasting can be used in a wide range of applications, and engineering. It is particularly useful when dealing with complex systems that are difficult to model using traditional forecasting methods. However, it is important to note that fuzzy-based forecasting is not a panacea and may not always produce accurate predictions. It should be used in conjunction with other forecasting methods and expert knowledge to improve the accuracy of predictions.

An alternative, also based on Fuzzy Set Theory and Fuzzy Logic, is fuzzy inference systems (FIS) [11], which are using the rule-based mechanisms that establish a relationship between series of input and output. There are 2 basic types of FIS, those are the Mamdani model [12] and the Takagi Sugeno Kang (TSK) model [13]; while fuzzification of variables input and application of operators in IF–THEN rules are the same in both condition of FIS, they mainly differ in terms of translating the fuzzy outputs inferred from the fuzzy rules into crisp values. The Mamdani type has better interpretation ability, whereas that TSK type has more better approximation accuracy. Two-well-developed approaches to FIS are adaptive network based fuzzy inference system or ANFIS [11], and the type-1 fuzzy FIS [14]. ANFIS employs TSK-type FIS in a 5-layered network structure, but the computationally process are expensive and generates complex models for even relatively simple problems. Main problem with the fuzzy-based time series forecasting models are came from the difficulty process of constructing and deconstructing the fuzzy sets, and also from the complexity of the FLRs [15]. A competitive strategy to overcome these difficulties consists of using several type of hybridization together with the fuzzy components. Among others, evolutionary algorithms, fuzzy clustering, artificial neural networks, particle swarm optimization and rough set rule induction have been successfully applied to different steps of FTS forecasting, especially for partitioning the UoD, fuzzification and defining FLRs [16–19].

2. Methodology

A. System Design

The research output will be a predictive system based on actual data. The forecasting system enables the prediction of power load based on several parameters such as time of day, weekdays, or weekend days. Sensors acquire the electrical load measurement and sent it to the server. The server processed and forecast electrical load. The Forecasting system is coded using python. Results are presented on the webserver which can be accessed by a phone or PC. A simple block diagram presenting the workflow can be seen in Fig. 1.

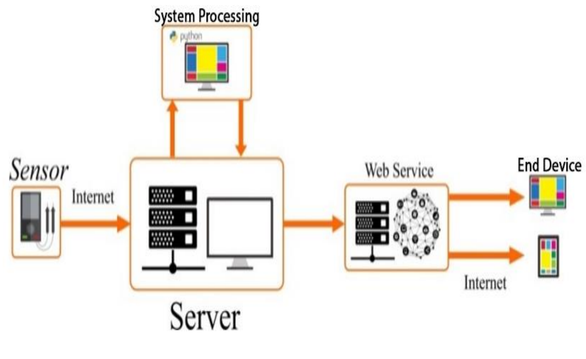

Fig. 1. System Design

B. Data Logging

Data from the sensors (frequency, amperage, voltage, and wattage) are kept in the server database. Data are collected from June 15th until July 12th, 2020 from load in Building H Electrical Engineering Department, University of Lampung. Training data then used to train a forecasting system. To predict electrical load, Fuzzy logic is used in the forecasting system. The forecasting will be classified into many classes according to the power load at any given time.

C. Past Data

Past data is data collected in the past. This data is used in the forecasting system to increase the performance of the forecasting. In this system, we allowed up to three weeks of past data to update forecasting.

D. The Forecasting System

Data is collected then processed using fuzzy logic approach. Load data is time tag with the time of the day, and date of the month. The fuzzy logic approach is done with a target of average Forecasting error below 30%. Mamdani's fuzzy approached steps are fuzzification, rules composition, and defuzzification [20].

E. Average Forecasting Error

The prediction in the forecasting system is checked for error. Two types of errors are evaluated in the forecasting system: Average Prediction Error (APE) and mean Average Prediction Error (mAPE). The APE and mAPE formulas are displayed in Fig. 2.

$$APE = \left|\frac{X_t - \widehat{X_t}}{X_t}\right| \times 100\% \quad (1)$$

$$\text{mAPE} = \frac{1}{T}\sum \left(\frac{X_t - \widehat{X_t}}{X_t}\right) \times 100\% \quad (2)$$

with:

Xt = i-th actual data

Ẍt = i-th prediction

3. Result and Discussion

A. Design of Fuzzy Approach

The forecasting system variables are load, time, and day as variables. Memberships are divided into 21. Memberships are used for accurate prediction. Fuzzy membership function is displayed in Fig. 2. These memberships are forming triangular shape membership function start from 0 watts to 2000 watts.

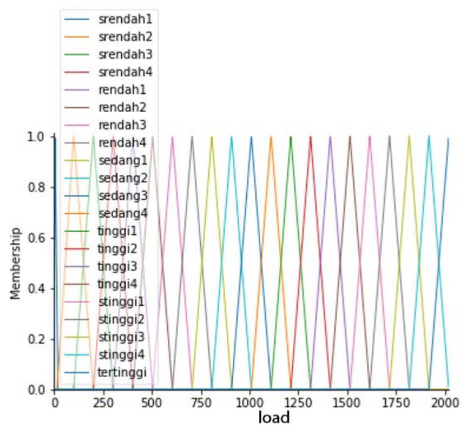

Fig. 2. Load Fuzzy Membership Function

Time is divided into three different membership types. The memberships function is divided into “pagi” or morning, “siang” or noon and the last one is “malam” or night. The sigmoid membership function is used for “pagi” membership, while the Gaussian membership function is used for “siang” membership and Pi membership function for the “malam” one. The membership function for the time of day is displayed in Fig. 3.

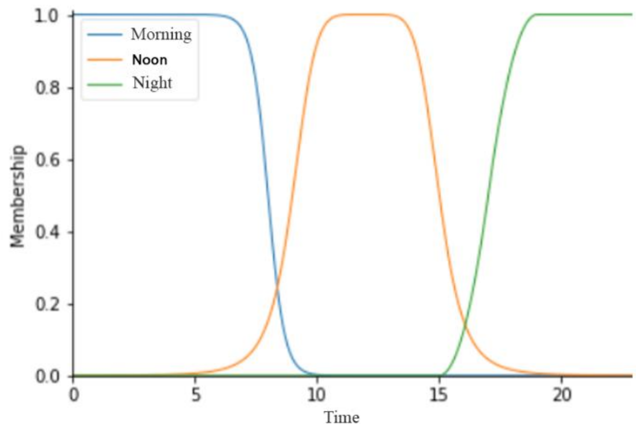

Fig. 3. Time of Day Membership Function

Days of the week differentiated into Weekdays minus Friday, Friday, and Weekends. The membership function for Weekdays minus Friday will be the trapezium membership function. While, for Friday will be a triangular shape membership function, and for Weekend will also be a trapezium membership function. The days of the week membership function is displayed in Fig. 4.

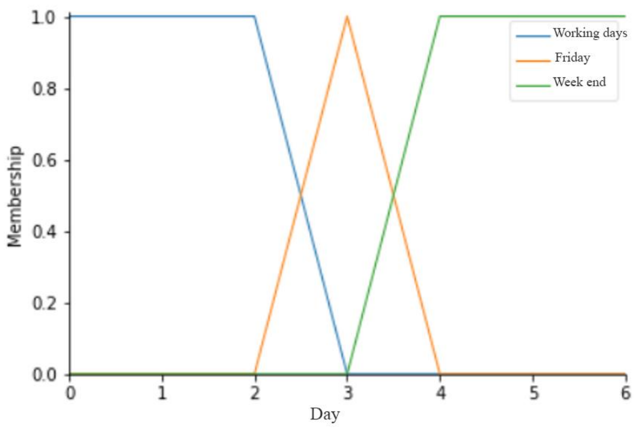

Fig. 4. Membership Function of Days of the Week

Forecasting variables use a triangular shape membership function and will be divided into 21 members. Memberships are used to increase the accuracy of the Forecasting. The memberships are “srendah”/very low, “rendah”/low, “sedang”/medium, “tinggi”/high, “stinggi”/very high, and “tertinggi”/highest. The membership function for Forecasting is displayed below. The memberships start from 0 watts up to 2000 watts.

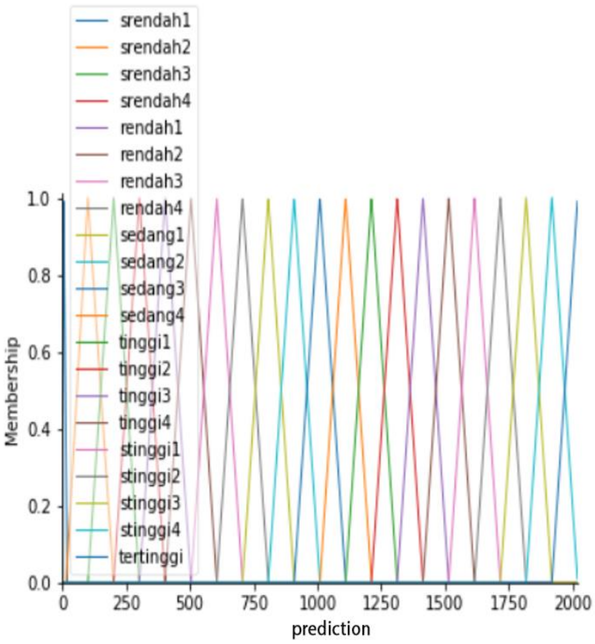

Fig. 5. Membership Function for Load Forecasting

B. Fuzzy Logic Rules Applied to The System

Fuzzy rules of the system are tweaked many times. The rules adhere to the load requirements in the Building H Electrical Engineering Department of Lampung University. There are 189 rules. Some of the rules are displayed in Table 1.

Table 1. Fuzzy Logic Rules in This System

	Load		**Time**		**Day**		**Forecasting**
IF	Srendah	AND	morning	AND	workday	THEN	srendah
IF	Rendah	AND	noon	AND	workday	THEN	rendah
IF	Sedang	AND	noon	AND	workday	THEN	sedang
IF	Srendah	AND	night	AND	workday	THEN	srendah
IF	Srendah	AND	morning	AND	friday	THEN	srendah
IF	Rendah	AND	noon	AND	friday	THEN	rendah
IF	Sedang	AND	noon	AND	friday	THEN	sedang
IF	Srendah	AND	night	AND	friday	THEN	srendah
IF	Srendah	AND	morning	AND	weekend	THEN	srendah
IF	Sedang	AND	morning	AND	weekend	THEN	sedang
IF	Rendah	AND	noon	AND	weekend	THEN	rendah
IF	Srendah	AND	night	AND	weekend	THEN	srendah

C. Load Forecasting

The forecasting system tested with the last three weeks' data. To Calculate the forecasting error, the forecasting result is compared to the actual measurement. One week of forecasting results is shown in this paper. Forecasting started on Monday, July 6th, 2020, and ended on Sunday, July 12th, 2020. In a week, there are three types of days: Weekdays minus Friday, Friday, and Weekends.

Forecasting is based on the last three weeks' data on the same day. The Weekdays minus Friday forecasting is displayed in Table 2. Forecasting error is calculated based on actual data collected on those days.

Table 2. Load Forecasting on Weekdays minus Friday (Sample Forecasting: Monday, July 6th 2020)

Time of Day (Hour)	**Forecasting (watt)**	**Actual Measurement (watt)**	**Forecasting Error (%)**
00	163,491	171,970	4,929
01	173,157	176,155	1,701
02	180,835	197,614	8,490
03	181,086	180,052	0,574
04	189,865	207,435	8,470
05	256,350	250,345	2,398
06	842,014	814,716	3,350

07	1448,167	1743,710	16,949
08	1327,904	1647,133	19,380
09	1868,424	2078,218	10,094
10	1930,358	2105,408	8,314
11	1816,352	1939,366	6,343
12	1681,167	1800,824	6,644
13	1770,946	1625,150	8,971
14	1749,556	1788,622	2,184
15	1611,559	1515,696	6,324
16	835,386	818,520	2,060
17	104,395	117,421	11,093
18	103,626	96,859	6,986
19	103,590	102,367	1,195
20	103,543	99,826	3,723
21	116,801	115,218	1,374
22	137,078	161,062	14,891
23	142,4308	170,350	16,389
		APE (%)	7,201

Monday, July 6th, 2020, the peak load is predicted at 10:00 WIB and coincides with the measured value peak load. But, the predicted load by the system produces an 8.31% error. The least forecasting error at 03:00 WIB with 0.57% error and the maximum error at 08:00 WIB with 19.38% error. On average, the load forecasting error on that day was 7.20%. Fig. 6 is displayed how close the load forecasting result against the measured load.

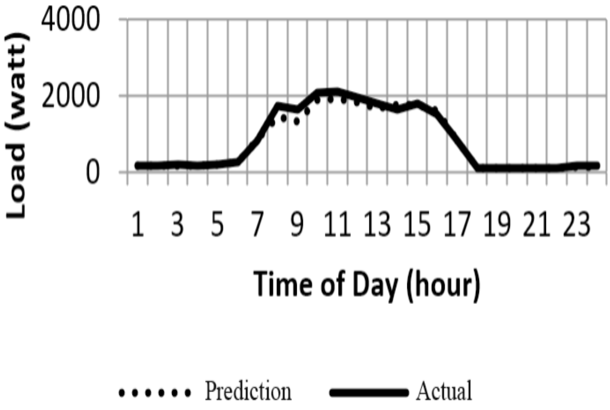

Fig. 6. Load Forecasting Result Againts the Measured Load on Monday, July 6th, 2020

Forecasting on Friday is based on the last three weeks' data on Friday. The Load Forecasting on Friday is displayed in Table 3.

Table 3. Load Forecasting on Friday (Sample Forecasting: Friday, July 10th 2020)

Time of day (Hour)	**Forecasting (watt)**	**Actual Measurement (watt)**	**Forecasting Error (%)**
00	174,779	161,705	8,085
01	158,571	159,784	0,758
02	144,341	145,889	1,061
03	164,012	163,375	0,390
04	185,644	171,208	8,431
05	211,928	221,854	4,473
06	763,698	818,407	6,684
07	2441,173	2102,617	16,101
08	2034,892	2145,961	5,175
09	2122,685	2222,624	4,496
10	2222,904	2188,851	1,555
11	2282,879	2293,827	0,477
12	2304,005	2160,654	6,634
13	2272,186	1931,375	17,646
14	2251,026	2019,890	11,442
15	2075,412	2226,755	6,796
16	1363,588	1606,075	15,098
17	191,644	174,0368	10,117
18	131,726	102,741	28,212

19	131,396	109,323	20,190
20	131,376	135,847	3,291
21	131,144	125,528	4,474
22	148,458	153,488	3,276
23	170,290	173,772	2,003
		Average Forecasting Error	7,786

Friday, July 10th, 2020, the peak load is predicted at 12:00 WIB and did not coincide with the measured value peak load at 11:00 WIB. The least Forecasting error at 03:00 WIB with 0.39% error and the maximum error at 18:00 WIB with 28.21% error. On average, the load Forecasting error on that day was 7.79%. Fig. 7 shown how close the load Forecasting results against the measured load.

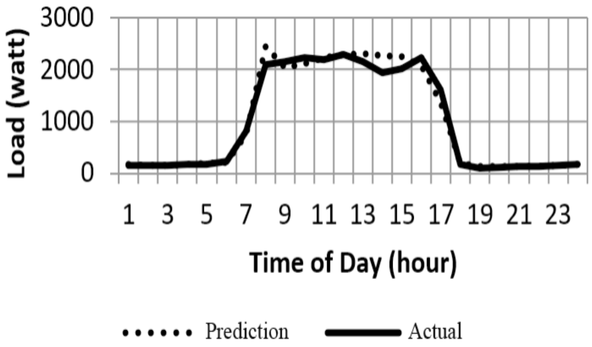

Fig. 7. Load Forecasting Result Againts the Measured Load on Friday, July 10th 2020

Forecasting on Weekends is based on the last three weeks' data on that given day. The Load Forecasting on Weekends is displayed in Table 4.

Table 4. Load Forecasting on Weekends (Sample Forecasting: Sunday, July 12th 2020)

Time of day (Hour)	Forecasting (watt)	Actual Measurement (watt)	Forecasting Error (%)
00	200,877	188,546	6,539
01	177,458	165,355	7,319
02	197,511	174,420	13,238
03	213,121	186,93	14,01
04	213,121	181,78	17,24
05	202,543	169,953	19,176
06	202,420	198,408	2,021
07	207,761	192,124	8,139
08	189,428	174,241	8,716
09	169,913	138,7416	22,467
10	136,211	117,993	15,439
11	89,387	97,773	8,577
12	81,424	98,161	17,05
13	73,834	94,215	21,632
14	79,521	91,966	13,532
15	87,995	93,107	5,491
16	92,921	86,6	7,298
17	81,682	91,197	10,432
18	83,308	99,692	16,434
19	99,242	116,19	14,586
20	107,2	114,652	6,500
21	119,954	116,831	2,673
22	122,807	110,870	10,766
23	139,481	144,758	3,645
		Average Forecasting Error	11,372

Sunday, July 12th, 2020, The peak load is predicted at 07:00 WIB and did not coincide with the measured value peak load at 06:00 WIB. The least Forecasting error at 06:00 WIB with 2.02% error and the maximum error at 09:00 WIB with 22.47% error. On average, the load Forecasting error on that day was 11.37%. Fig. 8 is displayed how close the load Forecasting result against the measured load.

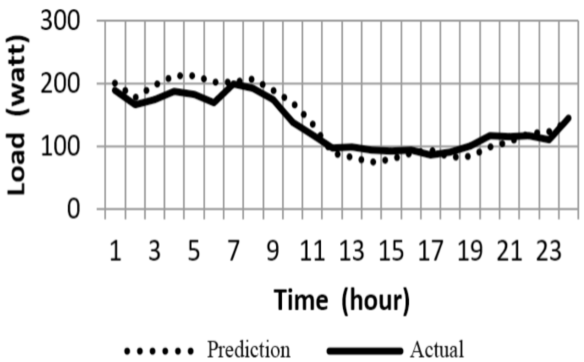

Fig. 8. Load Forecasting Result Against the Measured Load on Sunday, July 12th 2020

The load forecasting result on Weekdays minus Friday has a rising trend, starting at 05:00 WIB to 17:00 WIB and then declined. Load effectively happened during 05:00 WIB until 17:00 WIB. Load Forecasting on Friday somewhat follows the Weekdays minus Friday Forecasting. Although

Friday is set as a transition day, the results showed Weekdays minus Friday and Friday can merge into one membership as Weekdays. The Weekends Forecasting resulted in a slightly flat load. The Weekend's load forecast during the morning and noon rarely go higher than 200 watts. It is most likely because electricity is used partially in Building H. The average prediction error is 9.48%, which is moderately accurate to forecast total load at a certain period. During the COVID-19 pandemic, the system can be used to forecast load in the consumer residential. The system will allow an electrical officer to acquire measurement data remotely and adhering to the COVID-19 pandemic restrictions.

Load forecasting systems are displayed as charts on the online web monitoring system Lampung of University. The website developed using the Highchart library and Web Service. It is publicly available at http://uirg.unila.ac.id/mons/panel3.html. Fig. 9 displayed the Load Forecasting System.

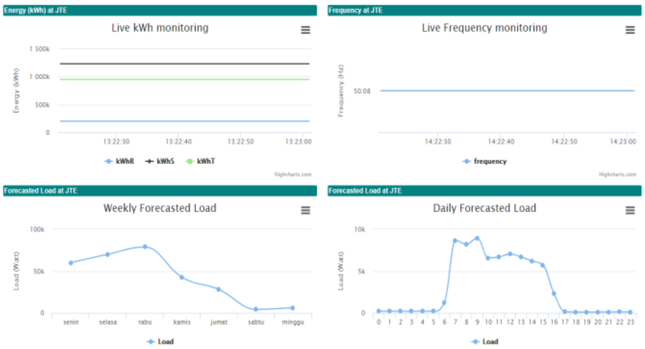

Fig. 9. Online Monitoring System of Lampung University

4. Conclusions

A fuzzy-based load forecasting system successfully built with a maximum forecasting error under 30%. The mAPE is 28.84%. The APE is 9.48%, moderately accurate to forecast periodic load. The system allows users to monitor and predict electrical load usage regardless of time and place. The system enables users to monitor and predict electrical load usage unrestrained by time and place. And, for the electrical officer, an easier way to know the electrical load measurements.

References

[1] Despa, D., Hakim, L., Syafruddin, M., 2014. Metode Regresi Linier untuk Prediksi Kebutuhan Energi Listrik Jangka Panjang (Studi Kasus Provinsi Lampung. Lampung: JITET vol. 2 no. 2 2014.

[2] Despa, D., Kurniawan, A., Komarudin, M., & Nama, G.F., 2015. Smart Monitoring of Electrical Quantities Based on Single Board Computer BCM238. 2nd International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE).

[3] Despa, D., Nama, G.F., Komarudin, M. & Zontche, M., 2016. Multi-Area Smart Monitoring of Electrical Quantities on Single Board Computer BCM2835. International conference EECCIS, Malang, Indonesia.

[4] Despa, D., Nama, G.F., Muhammad, M.A., & Anwar, K., 2017. The Implementation of Internet of Things (IoT) Technology in Real Time Monitoring of Electrical Quantities. IOP Conference Series: Materials Science and Engineering Vol 335 No 1.

[5] Despa, D., Nama, G.F. 2018. An Enhanced K-Means Clustering Algorithm for Pattern Discovery in Big Data Analysis of 3-Phase Electrical Quantities. International Journal of Engineering &Technology (IJET) Vol 7 Issue 4.36.

[6] Despa, D., Nama, G.F., Setiawan, Fx., A., & Delano, J., 2019. Artificial Neural Network Applications Use Measurements of Electrical Quantities to Estimate Electric Power. Journal of Physics: Conference Series Vol 1376 Issue 1.

[7] Ali, A.T., Elisa, B.M., Shamseldin, Z.M., 2016. Short Term Load Forecasting Using Fuzzy Logic. Sudan: IJAETMAS

[8] Dewi, S.K., 2010. Neuro-Fuzzy: Integrasi Sistem Fuzzy dan Jaringan Syaraf. Yogyakarta: Graha Ilmu

[9] Widodo, T.S, 2005. Sistem Neuro Fuzzy untuk Pengolahan Informasi, Pemodelan, dan Kendali. Yogyakarta: Graha Ilmu.

[10] Singh, S.K., 2009. Database System Concepts, Design, and Application. New Delhi: Dorling Kindersley.

[11] Mamdani, E.; Assilian, S. An experiment in linguistic synthesis with a fuzzy logic controller. Int. J. Man-Mach. Stud. 1975, 7, 1–13.

[12] Takagi, T.; Sugeno, M. Fuzzy identification of systems and its applications to modeling and control. IEEE Trans. Syst. Man.Cybern. 1985, SMC-15, 116–132.

[13] Jang, J.S. ANFIS: Adaptive-network-based fuzzy inference system. IEEE Trans. Syst. Man, Cybern. 1993, 23, 665–685.

[14] Tak, N. Type-1 possibilistic fuzzy forecasting functions. J. Comput. Appl. Math. 2020, 370, 112653.

[15] Singh, P. High-order fuzzy-neuro-entropy integration-based expert system for time series forecasting. Neural Comput. Appl. 2017, 28, 3851–3868.

[16] Cagcag Yolcu, O.; Alpaslan, F. Prediction of TAIEX based on hybrid fuzzy time series model with single optimization process.Appl. Soft Comput. 2018, 66, 18–33.

[17] Cai, Q.; Zhang, D.; Zheng, W.; Leung, S.C. A new fuzzy time series forecasting model combined with ant colony optimization and auto-regression. Knowl.-Based Syst. 2015, 74, 61–68.

[18] Egrioglu, E.; Aladag, C.H.; Yolcu, U. Fuzzy time series forecasting with a novel hybrid approach combining fuzzy c-means and neural networks. Expert Syst. Appl. 2013, 40, 854–857.

[19] Teoh, H.J.; Cheng, C.H.; Chu, H.H.; Chen, J.S. Fuzzy time series model based on probabilistic approach and rough set rule induction for empirical research in stock markets. Data Knowl. Eng. 2008, 67, 103–117.

[20] E.H. Mamdani and S. Assilian. An experiment in linguistic synthesis with a fuzzy logic controller. International Journal of Man-Machine Studies, 7(1):1-13. 1975