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The Effect of External Factors on Consumption Electricity Loads Forecasting using Fuzzy Takagi-Sugeno Kang

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***Abstract*—.This study applied Fuzzy Inference SystemSugeno to forecast electrical load by considering the external factors. To see the accuracy of forecasting using Fuzzy Inference System Sugeno, then a comparison between the forecasting results of Fuzzy Inference SystemSugenousing historical data with Fuzzy Inference SystemSugeno using external factors was done. By using external factors method, resulted the smallest RMSE of 0762 and using historical data obtained error (RMSE) of 1028. The results of the study came to the conclusion that Fuzzy Inference System Sugenomethod using external factors to forecast the consumption of electrical load givesa better result than Fuzzy Inference SystemSugeno using only historical data.**

***Index Terms*—Fuzzy Inference System Sugeno, external factors, consumption of electrical load forecasting.**

I. BACKGROUND

Electrical load consumption is an important activity particularly in the electricity providers sector. Without any accurate picture in the future, which may be based on the past, more than the capacity or lack of power can lead to unexpected high costs [1].

People's daily activities have increased in terms of electricity consumption. This is because electricity becomes an important part of people's daily activities. Demand increasing of electricity requires PLN as the electricity provider in Indonesia can supply the electricity needs appropriately so that the continuity of people’s multi fields can be assured.

Indonesia is located on the equator which causes the temperature in Indonesia is highest among the other regions on this earth. This thing affects the habitual patterns of Indonesian society in facing that rising temperature. In modernization era many household equipment that use electricity to regulate the environment’s temperature, Air Conditioner (AC) for instance. The using of this equipment becomes the habitual pattern that is common for Indonesian society who has power consumption that is relatively large as compared to the power absorbed by the other electronic equipment. It is definitely affects the pattern of electricity consumption among Indonesian society.

Based on the various problem points of view required an electrical load forecasting in the society and in terms of the influence of external factors. So that the purposes of electrical load forecasting can be a part of electrical load projecting and help to estimate the power needs to be supplied by PLN to society.

Short-term load forecasting aims to estimate the electrical load at a period of minutes, hours, days or weeks [2]. Short-term load forecasting has an important role in real time control and security functions of an energy management system. A correct short-term electrical load forecasting is able to generate savings in operational costs and a secure condition that allows utilities to process production resources to optimize energy prices and exchange with producers and consumers.

In forecasting requires not only the electrical load data in the past to project the electrical load demand. Besides that, the electrical consumption can also be caused by other factors or external factors. According to Ling et al. [3] the electric load forecasting needs to consider the environmental temperature, especially for areas which have a high temperature such as Indonesia. The population is crucial thing in electrical load forecasting electricity [4]. Indonesia is one of the countries with the second densest population in ASEAN where the increasing of population will give a result to the increasing of human electrical needs. Pousinho et al. [5] reveals electricity tariffs are needed in short-term electrical load forecasting. From those several factors, the researchers used three (3) external factors to help in forecasting the electrical load consumption in order to improve the accuracy of forecasting.

Fuzzy logic is a study that studies about uncertainty which has the advantage that is the capability in the process of reasoning linguistically (linguistic reasoning). In the theory of fuzzy logic known a concept of fuzzy system that is used in the prediction process and generally consists of four stages: fuzzification (a conversion from crips into the form of fuzzy numbers), the establishment of the rule base (fuzzy rules base), inference systems / fuzzy reasoning, and defuzzification (conversion of fuzzy numbers resulted from fuzzy

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inference process in to the form of crips). Fuzzy inference methods that are generally used are Mamdani, Sugeno and Tsukamoto. But in this study fuzzy inference method used was the Sugeno inference method because researchers wanted to involve a linear equation to forecast the electrical load consumption with the concept of fuzzy logic [6]. Linear equation used was multiple linear regression equation.

In this study, the researchers want to know the electrical load consumption forecasting in 2011, where the electrical load consumption was predicted using fuzzy logic with Sugeno fuzzy inference system involving external factors. Furthermore, the results of electrical load consumption forecasting with that fuzzy logic were compared to the actual values.

II. RELATED STUDIES

This study aims to forecast the electrical load consumption by using fuzzy approach. Chang et al [7] used fuzzy for stock trading. Results obtained using the Fuzzy TSK was TSK Model was able to capture the dynamic and complex and could be used to forecast the stock trading average in real-time. TSK model can be used to forecast more accurately as compared to Regression [8].

The importance of electrical load consumption forecasting is shown in several studies. Suppose the study by Haviluddin et al. [9] using Regression model such as ARIMA that often implemented for forecasting. In this study, ARIMA is for forecasting the activity of a network. The results of ARIMA model implementation for forecasting tended to be constant that was only capable to read the historical data from network activity. Barbulescu et al. [10] used Artificial Neural Network (ANN) to forecast the monthly electrical load. This study provides an accuracy of 65% as the results. But there are shortcomings resulted in the using of ANN to forecast the electrical load. Random weighting gives the forecasting results which are still less optimum or away from the target due to the random method in determining at the beginning.In their study, Santika et al. [11] introduced a new hybrid model neuro-fuzzy, and evaluate its performance in estimating the short-term energy load. A total of two intelligent forecasting systems were tested and compared, namely: neural networks and neuro-fuzzy.

Fuzzy gave a big influence to the forecasting results with this method revealed the potential of neuro-fuzzy model proposed to estimate the load with the final accuracy result was 98%.

Based on the results of several studies that have been done, progressively calculation using the categories Block I, Block II and Block III were considered to have weaknesses that seem to be perceived less fair because of a very wide restriction.

Fuzzy method offers a more equitable tariff with the sense of its smoother limit, so that the categorization is no longer needed. This study will examine the electrical load by Fuzzy Sugeno method. The examining data are the data load of the power consumption (KWh) used by the customers, temperature (C), and Population.

III. FACTORS THAT AFFECT ELECTRICAL LOAD FORECASTING

Theory about electrical load and factors that affect the electrical load has been discussed by Sukirno, [25]. Those factors include the following:

1. Number of Population
   The population growth has a major influence on the electrical energy needs in addition to economic factors. Residents will rise each year until at some point will be in a stable condition
2. Weather
   Factors weather including temperature, humidity, wind speed, cloud state, and light intensity. The weather changes cause changes to consumer convenience and affects the use of equipment. One influential factor is the temperature. The conductor is one of the most important components of the electrical power distribution system. The ability of a conductor in the electric current is influenced by the temperature around the conductor. Temperatures around the conductor will cause changes in the conductivity of the conductor; the greater the conductivity conductor temperature will be smaller
3. Electrical Tariff
   If in an economy experiencing inflation, the real income of the community is changing. It has an impact on the consumption of electricity load. Nominal consumption will have no effect, but consumption will decline in real terms.
4. Gross Domestic Product (GDP)
   Passing of regional development will be greatly influenced by the economy of the region itself. In this case, either directly or indirectly. The economic factor is very influential on the electrical energy needs as development progresses. Local government as the implementers of government at the local level will take on an important role in regional development planning. It shaped the policy contained in various products of local regulations. This includes the planning of land use, industrial development, territorial, settlement and geographical factors

IV. FUZZY INFERENCE SYSTEM

1. Fuzzy Logic
   Fuzzy Logic is basically an appropriate way to map the input room into an output room. In fuzzy logic known a condition from "0" to "1" [10]. In crisp set, the membership value on an item x in an A set is written μA[x]. In this study, using a representation of the trapezoidal-shape membership function to determine the degree of membership. Trapezoidal-shape membership function used because it is relatively simple as an example on the previous study that has been conductedby Muzayyanah [8] in the caseof raw material supply determination in helping industry marketing target with FIS Sugeno method.

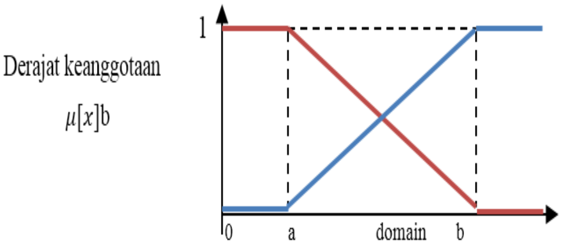

Figure 1. Representation of input variable membership set function.

2. Sugeno Method
Fuzzy Sugeno method is a fuzzy inference method for rules that are represented in the form of IF - THEN, where system output (consequent) is not in the form of fuzzy sets, but in the form of a constant or linear equations. This method was introduced by Takagi-SugenoKang in 1985 [7]. Sugeno model uses Singleton membership function namely the membership function which has a degree of membership 1 in a single crisp value and 0 in other crisp values that. For Order 0 by the formula:

IF (x1 is a1) ° (x2 is A2) °…°(xn is An) THEN z= k,

with Ai is the fuzzy set to i as an antecedent (reason), ° is the fuzzy operator (AND or OR) and k is crisp constant as consequent (conclusion).

While Order 1 formula is:

*IF (x1 is a1) ° (x2 is A2) °…°(xn is An) 10 THEN z = p1*x1+…+pn*xn+q,*

with Ai is the fuzzy set to i as an antecedent, ° is the fuzzy operator (AND or OR), pi is a constant to i and q is also a constant in the consequent.

3. Fuzzy Sets Formation
a. Input variable
In this study involved two types of input variables, the first historical data of electrical load consumption using timelag t-1 for an hour before, t-2 for two hours before and t-3 for three hours before. Second, by adding external factors such as temperature and population with the aim of this study wanted to know how big the influence of external factors to the electrical load consumption was. So that the criteria used to forecast electrical load as fuzzy rules were five criteria.
b. Define Fuzzy variable
In fuzzy logic, the triangle membership function is a combination of the two lines (linera) used to determine the degree of membership. Below is a representation of the membership function owned by input variable t-1 historical data shown in Figure 2.

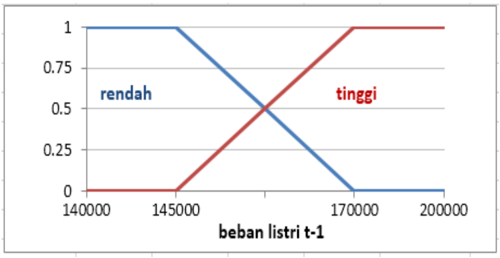

Figure 2. Representation of input variable membership set function.

Membership function on each input variables where μ is the degree of membership and x is the input value to be converted into fuzzy sets are described as follows:

$$\mu pmtRendah[x] = \begin{cases} 1 & x \leq 145000 \\ \frac{170000 - x}{170000 - 145000} & 145000 \leq x \leq 170000 \\ 0 & x \geq 170000 \end{cases} \quad (1)$$

$$\mu pmtTinggi[x] = \begin{cases} 0 & x \leq 170000 \\ \frac{x - 145000}{170000 - 145000} & 145000 \leq x \leq 170000 \\ 1 & x \geq 170000 \end{cases} \quad (2)$$

c. Output variable
Output variable in this study was in the form of clustering which was the result of the electrical load consumption forecasting.

d. Fuzzy Sets Rule
This stage aimed to build the fuzzy rules, where the results of the calculation process would be inferenced to the fuzzy rules which had been built before. In building the fuzzy rules depends on the number of fuzzy sets and parameters used. For example, if there are 4 parameters or input variable with two fuzzy sets each, then the number of rules created is 2 to the power 4; where the value of 2 is the number of fuzzy set, whereas the value of 4 is the number of all parameters. In establishing the fuzzy rules of FIS Sugeno model, there are antecedent and consequent. Consequent in this fuzzy model used regression equations, where each coefficient would be multiplied by any parameters or input variables. According to Cox (1994), Order One fuzzy Sugeno for inference system fuzzy Sugeno is:

*IF((x1 is A1) AND (x2 is A2) AND (x3 is A3) …. (xnisAn)) THEN z=p1*x1 +p2*x2 +p3*x3+ …+pn*xn + q*

where Ai is the i^{th}fuzzy set as antecedent, pi is the i^{th} constant (crisp) and q a constant in the consequent. The next stage was defuzzification on the results of fuzzy Sugeno inference system by calculating the weighted average:

$$Z^* = \frac{\sum_{i=1}^{n} w_i z_i}{\sum_{i=1}^{n} w_i} \text{dimana : } w_i = \prod_{j=1}^{m} \mu_{Pj}(x_j) \quad (3)$$

where zi is the output value of the i[th] basic rule consequent, wi is the results of a fuzzy set operation process in the antecedent, n is the number of rules that are used and value/ degree of membership of an x value in all the fuzzy set operations in the antecedent (Naba, 2009). The last stage was to do fitting fuzzy Sugeno model for electrical load consumption forecasting by using data testing. As for knowing the accuracy of forecasting Root Mean Square Error (RMSE) was used.

V. Results and Discussions

This study used a programming language Java, Netbeans 8:01 with PC-32 bit. External factors involved in order to determine the effect of those factors in forecasting. There were two testing in this study which were forecasting using external factors and forecasting using only electrical load consumption historical data.

a. The formation of external factors membership function

In fuzzification stage, each fuzzy variable in the input data was divided into two fuzzy sets, namely Low and High. All of the fuzzy sets each fuzzy variable in the input data was represented using the same membership functions that the trapezoidal-shape membership function.

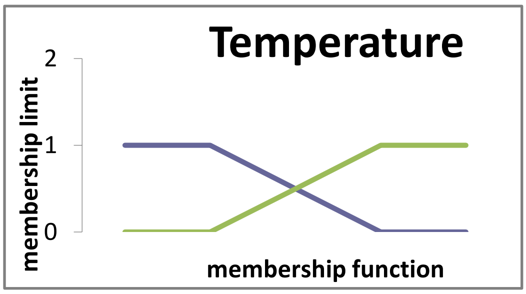

Figure 3. Representation of temperature variable input set membership function

$$\mu turun\,(x) = \begin{cases} 1 & x \leq 25 \\ \frac{40 - x}{15} & 25 < x < 40 \\ 0 & x \geq 50 \end{cases}$$

$$\mu naik\,(x) = \begin{cases} 0 & x \leq 25 \\ \frac{x - 25}{40} & 25 < x < 40 \\ 1 & x \geq 40 \end{cases}$$

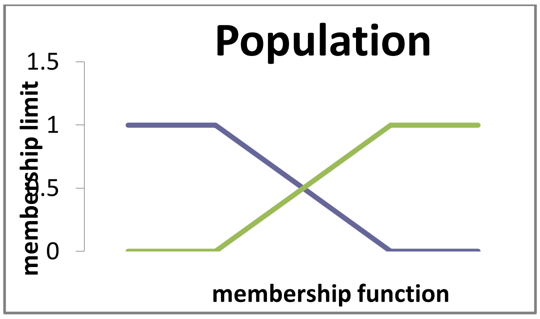

Figure 4. Representation of population variable input membership function

$$\mu turun\,(x) = \begin{cases} 1 & x \leq 198700 \\ \frac{206000 - x}{198700} & 198700 < x < 206000 \\ 0 & x \geq 210000 \end{cases}$$

$$\mu naik\,(x) = \begin{cases} 0 & x \leq 198700 \\ \frac{x - 198700}{206000} & 198700 < x < 206000 \\ 1 & x \geq 206000 \end{cases}$$

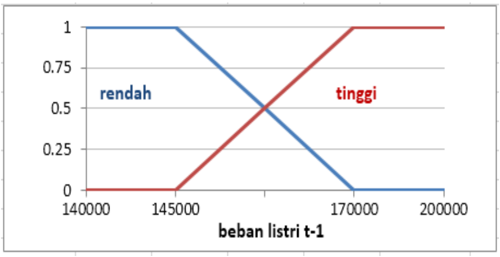

Figure 5. Representation of t-1 variable input set membership function

$$\mu turun\,(x) = \begin{cases} 1 & x \leq 140000 \\ \frac{198000 - x}{10000} & 140000 < x < 198000 \\ 0 & x \geq 198000 \end{cases}$$

$$\mu naik\,(x) = \begin{cases} 0 & x \leq 140000 \\ \frac{x - 140000}{10000} & 140000 < x < 198000 \\ 1 & x \geq 198000 \end{cases}$$

b. The Formation of Basic Rule

The basic rule of fuzzy formed for the electrical load consumption on Order One Sugeno models as many as 32. The following is an example of the rule that form in Table 1.

Table 1. The basic of fuzzy rule

*IF Y(t-1) Tinggi AND Y(t-2) Tinggi AND Y(t-3) Tinggi AND Y(temperature) Tinggi AND Y(populasi) THEN a + b1 * Y(t-1) + b2 * Y(t-2) + b3 * Y(t-3) + b4 * Y(temperature)+ b5 * Y(populasi)*
*IF Y(t-1) Tinggi AND Y(t-2) Tinggi AND Y(t-3) Rendah AND Y(temperature) Rendah AND Y(populasi) THEN a + b1 * Y(t-1) + b2 * Y(t-2) + b3 * Y(t-3) + b4 * Y(temperature)+ b5 * Y(populasi)*
*IF Y(t-1) Rendah AND Y(t-2) Rendah AND Y(t-3) Rendah AND Y(temperature) Rendah AND Y(populasi) THEN a + b1 * Y(t-1) + b2 * Y(t-2) + b3 * Y(t-3) + b4 * Y(temperature)+ b5 * Y(populasi)*
*IF Y(t-1) Rendah AND Y(t-2) Rendah AND Y(t-3) Tinggi AND Y(temperature) Tinggi AND Y(populasi) THEN a + b1 * Y(t-1) + b2 * Y(t-2) + b3 * Y(t-3) + b4 * Y(temperature)+ b5 * Y(populasi).*

Some of the notations used are:
[*Aj] is the interval appropriate touj
membership to$Aj$is supremum(that is 1)
L [*Aj] is the lower limit of interval uj
U [*Aj] is the higher limit of interval uj
l[*Aj] is the length of interval ujwhose membership in $Aj$is supremum(that is 1)
M [*Aj] is the middle value of interval uj which hasSupremum value Aj.
For fuzzy logical relationship $Ai \rightarrow Aj$:
Ai : fuzzification load value on the day $n-1$
Aj: fuzzification load value on the day n
Ei: the actual load value on the day $n-1$
$Ei-1$: the actual load value on the day$n-2$
$Ei-2$: the actual load value on the day$n-3$
Fj : the forecasting crips load value on the day n

Order one model utilizing historical data on the day n-3, n-2, n-1 to frame the implementation rules of fuzzy logical relation Ai → Aj, with Ai is fuzzification load value on the day *n-1* and Aj is fuzzification load value on the day *n*. The proposed method for forecasting mentioned as a rule to produce a relationship between time series on the day n-3, n-2, n-1 to forecast enrollments on the day n.

Rules : forecast for the day n and beyond. The following is the pseudo code of the rule formation on fuzzy Sugeno:

```
Ai → Aj
Compute
Di = ||(Ei - Ei-1)| -|(Ei-1 - Ei-
2)||
Xi = Ei + Di/2
XXi = Ei - Di/2
Yi = Ei + Di
YYi = Ei - Di
For I = 1 to 4
If Xi ≥ L [*Ai] And Xi ≤ U [*Ai]
Then P1 = Xi; n = 1
Else P1 = 0; n = 0
Next I
If XXi ≥ L [*Ai] And XXi ≤ U [*Ai]
Then P2 = XXi; m = 1
Else P2 = 0; m = 0
Next I
If Yi ≥ L [*Ai] And Yi ≤ U [*Ai]
Then P3 = Yi; o = 1
Else P3 = 0; o = 0
Next I
If YYi ≥ L [*Ai] And YYi ≤ U [*Ai]
Then P4 = YYi; p = 1
Else P4 = 0; p = 0
B = P1 + P2 + P3 + P4
If B = 0 Then Fj = M [*Aj]
Else Fj = (B + M [*Ai])/(m + n +
o + k + 1)
  Next k
```

That basic rule of the fuzzy then was inferenced by Sugeno fuzzy inference system that used Order One Sugeno model. After that, defuzzification was done to obtain an output value of inflation as a forecasting result. This defuzzification process was performed on training and testing data. Defuzzification on training data was done to determine how well the fuzzy Sugeno model in forecasting electrical load consumption was. The model testing results on the training data indicated that fuzzy Sugeno model was very well in electrical load consumption forecasting for the data patterns from the forecasting result followed the pattern of its actual data.

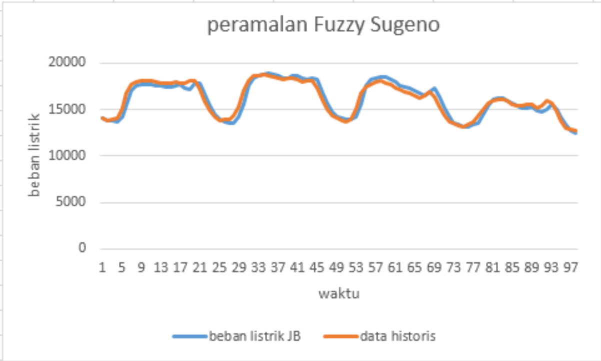

Figure 6. The forecasting result by using historical data (t-1, t-2, t-3)

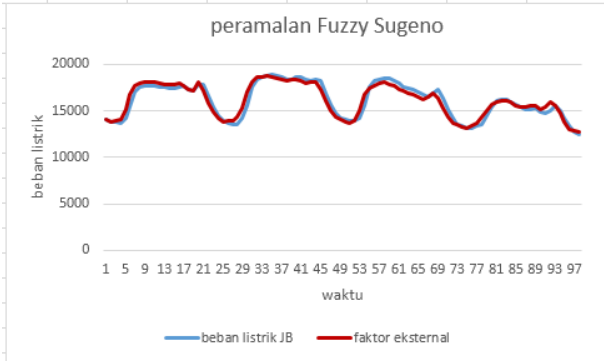

Figure 7. The forecasting result by using temperature and population as external factors

From Figure 6 and Figure 7 show the different plot results of the electrical load consumption forecasting. In Figure 6 electrical load consumption forecasting by using historical data input variable t-1, t-2 and t-3 whereas in Figure 7 using additional external factors, namely temperature and population. From the plot results, it is clear that with the addition external factors affect the forecasting results. The results of forecasting then was calculated the error rate by using RMSE as in Table 2.

Table 2. The result of error calculation by using RMSE

Forecasting Method	RMSE
Fuzzy Sugenoby using historical data	1.028
Fuzzy Sugenoby using external factors	0.762

In Table 2 provides evidence that electrical load forecasting by considering external factors gives influence to the forecasting results in the case of electrical load. RMSE result using external factors was 0762 by comparison the forecasting using historical data only was 1,028.

VI. Conclusions and Suggestions

6.1 CONCLUSIONS

Fuzzy Inference System Sugeno method can be applied to forecast electrical load consumption. Tests conducted on the value from experts with fuzzy calculation gives a strong relationship with the actual data with RMSE values for 0.762.

6.2 SUGGESTIONS

For further study, the researchers suggested for optimizing the fuzzy rule so that the level of validity or accuracy is higher using heuristic algorithms such as evolutionary algorithm which is proven to be successfully applied to various optimization problems [13].

REFERENCES

[1] V. Ş. Ediger and S. Akar, “ARIMA forecasting of primary energy demand by fuel in Turkey,” *Energy Policy*, vol. 35, no. 3, pp. 1701–1708, Mar. 2007.

[2] K. Metaxiotis, A. Kagiannas, D. Askounis, and J. Psarras, “Artificial intelligence in short term electric load forecasting: a state-of-the-art survey for the researcher,” *Energy Convers. Manag.*, vol. 44, no. 9, pp. 1525–1534, 2003.

[3] H. Yi-Ling, M. Hai-Zhen, D. Guang-Tao, and S. Jun, “Influences of Urban Temperature on the Electricity Consumption of Shanghai,” *Adv. Clim. Change Res.*, vol. 5, no. 2, pp. 74–80, 2014.

[4] Suhono and Sarjiya, “Long-term Electricity Demand Forecasting of Sumatera System Based on Electricity Consumption Intensity and Indonesia Population Projection 2010-2035,” *Energy Procedia*, vol. 68, pp. 455–462, Apr. 2015.

[5] H. M. I. Pousinho, V. M. F. Mendes, and J. P. S. Catalão, “Short-term electricity prices forecasting in a competitive market by a hybrid PSO–ANFIS approach,” *Int. J. Electr. Power Energy Syst.*, vol. 39, no. 1, pp. 29–35, Jul. 2012.

[6] H. Mori, Y. Sone, D. Moridera, and T. Kondo, “Fuzzy inference models for short-term load forecasting with tabu search,” in *Systems, Man, and Cybernetics, 1999. IEEE SMC’99 Conference Proceedings. 1999 IEEE International Conference on*, 1999, vol. 6, pp. 551–556.

[7] P.-C. Chang, J.-L. Wu, and J.-J. Lin, “A Takagi–Sugeno fuzzy model combined with a support vector regression for stock trading forecasting,” *Appl. Soft Comput.*, vol. 38, pp. 831–842, Jan. 2016.

[8] A. Ghanbari, S. F. Ghaderi, and M. A. Azadeh, “Adaptive Neuro-Fuzzy Inference System vs. Regression based approaches for annual electricity load forecasting,” in *Computer and Automation Engineering (ICCAE), 2010 The 2nd International Conference on*, 2010, vol. 5, pp. 26–30.

[9] Haviluddin and A. R, “Forecasting Network Activities Using ARIMA Method,” *J. Adv. Comput. Netw. JACN*, vol. 2, pp. 173–179, Sep. 2014.

[10] C. Barbulescu, S. Kilyeni, A. Deacu, G. M. Turi, and M. Moga, “Artificial neural network based monthly load curves forecasting,” in *2016 IEEE 11th International Symposium on Applied Computational Intelligence and Informatics (SACI)*, 2016, pp. 237–242.

[11] Santika G.D, Mahmudy W.F, and Naba A., “Electrical Load Forecasting using Adaptive Neuro-Fuzzy Inference System,” International Journal Advance Soft Computing Its Application., 2016.

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