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Application of the Average Based Fuzzy Time Series Model in Predictions Seeing the Use of Travo Substations

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Abstract— This research is expected to be a reference for PT PLN in delivering information quickly in predicting the capacity of transformer substations in each region in the industrial area and dealing with increasingly rapid population growth. This study aims to analyze the power of each region's transformer substations so that it is more optimal in predicting usage loads and no imbalance and overload of electricity is not suitable for each region's transformer substation capacity. Applying an average-based fuzzy time series model can provide fast and accurate information following consumer expectations in predicting each need in each area and the number of load rating substations used by all consumers in each region. The research methodology employed is to collect data for each location of the distribution transformer to see the voltage at the end of the line. The next step is to look at data from each specification of the distribution transformers along with the locations of the distribution transformers that can be managed through the Development of a Mobile Device-Based Distribution Transformer Recording System at PT PLN. The results of this study in transformer power 100 consumption 99.43, unbalanced 28%, fuzzification A8, FLRG G8, forecasting results 10.69 with a Mape forecast value of 0.57%. Furthermore, the power consumption of transformer 50 is 36.70, unbalanced 78%, fuzzification A6, FLRG G6, forecasting results 23.91 with Mape 1.11%. Results with the smallest mape with each travo travo 50 in each usage area 28.43, unbalanced 26%, fuzzification A5, FLRG G5, forecasting results 23.91 with Mape 0.28%. This study's results can determine the transformer's location along with unbalance, overload and the estimated amount of power consumption load for the use of transformer substations in an area, especially the ULP PT.PLN area for each region in PT.PLN (Persero) Krueng Geukuh. The conclusion from the results of this study can be used as a reference for monitoring population growth with excessive transformer power loads so that in the future, PT PLN can install new transformer substations following the capacity of the number of customers in each region.

Keywords: Information Technology, Information Systems, Distribution Substations, Distribution Transformers

1. Introduction

Along with the increasing development of population and economic development, the need for electric power continues to increase from year to year. This is in line with the life activities of residents who depend on the availability of electricity supply. Therefore, it is urgently needed to provide a large and professional supply of electricity at affordable prices for the needs of the wider community. [1], [2], [3].

This study aims to determine the use of power and transformer capacity in each region according to the needs. Fuzzy time series model to forecast transformer substation movements every month based on building density and population. Finally, the forecasting model can see the position of the electrical substations and the area used for each.

In the current phenomenon of increasing electricity demand for residents, PT. PLN (State

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Electricity Company) as the main distributor of electricity to the people in North Aceh district. Obligation to carry out surgical planning and the need for planning an electric power development system in determining the stock of energy needs that will be distributed to the community. Then the target of electrical energy to be distributed is in accordance with the estimated costs that have been incurred. [4].

Planning an electric power development system to identify how much electrical energy must be distributed to consumers so that the electrical energy is distributed according to the required target [5]. [6] Fulfillment of electric power loads in Indonesia, one of which is in the PT Area customer service unit. PLN (PERSERO) Krueng Geukuh Customer Service Unit sometimes often experiences problems, which are faced with population density and there are rotating power outages in several sub-districts [7].[8],[9]

This is due to several problems in PLN's work environment, including the management of transformer maintenance which is still being processed manually, the complete installation of transformer data is not recorded, and the incompatibility of the installed transformer capacity load data with the electrical energy load distributed to customers. [10]. Transformers are a legacy of PLN at high prices, so management or a system for maintaining transformers is needed on a regular and continuous basis, so that they can increase payments for purchasing new transformers due to damage to a transformer. Transformer management is to be improved and to extend the operational life of transformers, so that a plan for the year of operation is needed, especially if it can exceed the energy expended by PT PLN, which can increase the suitability of community stock needs [11] [12]. The most important thing in this study is the position of the transformer which is designed in such a way as to be able to identify transformer data in the form of the route or the nearest road that leads to the position of the transformer in detecting community needs for sehor needs. By using the map box API technology which uses the concept of Location Based Service (LBS in viewing the user by seeing the needs of the pass in viewing data on the position of an area or object originating from the coordinates of its location.[13],[14]

Research in looking at FTS predictions of electricity consumption in decision making and can control stock needs for each region. This research can see data on the amount of electrical energy consumption in each region and can predict trend data for forecasting in each group. Testing with FTS can produce good grouping values with a Map After test value of 9.24. Then this study produces predictions of electricity consumption in Indonesia [15]. Further research with fuzzy time series models can predict the value of the basic electricity tariff for households which can be assessed by KWH electricity rates. The results of this study can predict tariff groups based on users/households [16]. Further research emphasizes forecasting in the industrial world to see the predictions presented in the long term for future needs. The results of this study are to compare the accuracy values for each year 2019-2027 by looking at the increase in population, education infrastructure, health infrastructure and the historical loading of the Jember Substation. Where this research aims to produce the optimal uprating time for transformers at the Jember Substation for the next 6 years. [17], [18].

2. Method

2.1 Research design

System analysis of consumption load as seen from the transformer substation with the average-based fuzzy time series method model for electricity consumption for each region at ULP Krueng. System analysis can monitor transformer power loads, and this research can help officers at ULP Krueng Geukuh install new transformers according to population growth. Then can analyze forecasting on forecasting at each substation which produces unbalanced and overloaded transformers in optimization time

The research method focuses on systems that are already running as an object of research. Beginning with data collection, data processing using the fuzzy time series method, data fuzzification to determine the FLR and FLRG values and determine the prediction results. These stages are illustrated in Figure 1.

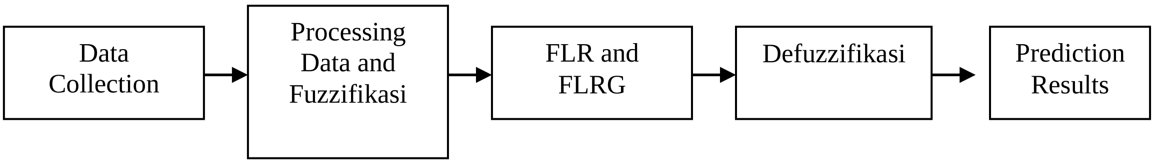

Figure 1. Research Methods

Data was collected using transformer usage load data recorded from 2019-2021 at PT. PLN (Persero) ULP Krueng Geukuh aims to test data for the prediction process of power consumption loads on transformers, and data for 2020 will be used to make predictions for 2021. The goal is for data testing for the prediction process for power consumption loads on transformers to make predictions for the year at the end of the year. The results of the transformer load data recorded from January 2020 to the end of October 2020 at PT. PLN (Persero) ULP Krueng Geukuh is used for data testing to predict power consumption loads on transformers. Data for 2020 will be used to make predictions for 2021 with calculations using the Average Based Fuzzy Time Series method.

In the research flow the first step is to collect datasets to then be processed using the fuzzy time series method [19] [20]. After the data is processed, the next step is to determine the prediction results where the prediction results reach the specified target or not.

2.1 Fuzzy Time Series

The Fuzzy time series method uses intervals with FLR (Fuzzy Logical Relationship) in the presence of a relationship and giving weights that are assessed based on the order of the weights [21] [22]. The FTS forecasting steps using the formula:

$$U = [d_{min}, dmax] \tag{1}$$

Where d_{min} is the smallest data while d_{max} is the largest data. Determination in looking at the value of the interval in determining the width of the interval as follows:

$$R = [d_{max}, d_{min}] \tag{2}$$

Where R is about the value, where d_{max} is the largest data while d_{min} is the smallest data. The determination of the class interval value is as follows:

$$K = 1 + 3{,}322 \ X \log n \tag{3}$$

Where K is the class interval and n is the number of data sets multiplied by the value 1+3.322 from the sturges rule to find the class interval value. The next step is to determine the width of the class interval with the following formula.

$$I = (\text{Range data } (R))/(\text{Number of class intervals } (2)) \tag{4}$$

The next step is how to determine the average value of the optimal fuzzy time series by examining the length of the size of the fuzzy sets that interact with each other during forecasting. [23].

The following is a prediction base mapping Table 1.

Table 1. Prediction Base Mapping

Range	Basis
0.1-10	0.1
1.1-10	1
11-100	10
101-1000	10

As for looking at the calculation of the difference in absolute value between Dt-1 and Dt (t=1, ..., n) where D is the actual information and t is the period. The next step is to determine the fuzzy set. If there is a relation R (t, t+1) then derive the formula:

Pers FLR Ai(t+1) = Ai(t) x R (t, t+1) (5)

Pers FLR II Ai(t) → Ai(t+1) (6)

The equation above can determine the value of Ai(t). Then the settlement of FLR values that have a range of Ai(t+1) and Ai(t). next is to determine the Fuzzy Logical Relationship Group (FLRG). [24], [25].

3. Result and Discussion

In this calculation, there are 10 sample data that will be calculated using the Average Based Fuzzy Time Series method. The data used is data on transformer usage load recorded from January 2020 to the end of October 2020 at PT. PLN (Persero) ULP Krueng Geukuh which aims to test data for the prediction process of the power consumption load on transformers and data for 2020 will be used to make predictions for 2021. The manual calculation of the transformer data prediction process is as Table 2.

Table 2. Datasets

No	Year 2020	Transfor mer Pow	Usage (%)	Unbalanced (%)
1.	Jan-20	100	99	28%
2.	Feb-20	50	73	37%
3.	Maet-20	50	57	100%
4.	April-20	50	57	26%
5.	May-20	50	28	48%
6.	Jun-20	50	69	55%
7.	Jul-20	25	58	63%
8.	Agust-20	50	64	15%
9.	Sept-20	50	93	6%
10.	Oct-20	50	36	34%

The next step is to determine D_min and D_max. where the drinking value obtained is 3 and the maximum value obtained is 12 as in the following Table 3.

Table 3. Min Max Value

D_min	D_max
3	12

Where D_min is the smallest value and D_max is the largest value of the data. So that the universal set can be notated as follows. U = [3,122]. The next step is to determine the number of classes with the formula: Number of Classes = ROUND (1+3.22 * Log 10(321);0. The results obtained are 9 classes. With information 321 is the amount of data used for prediction while class length = (122 -3) ∶ 9=13,2. So that the results are obtained as in the following Table 4.

Table 4. Number of Classes and Class Length

MIN	MAX
3	122
D1	D2
3	22
MIN 1	MAX 1
0	100
Number of Classes	Class Length
9	13,22

The next step is to determine the lower limit, upper limit and middle value. As in the following Table 5.

Table 5. Upper, Lower and Middle Limit Values

No	Lower limit	Upper limit	Middle value
1.	0	12,22	6,11
2.	13,22	25,44	25,94
3.	26,44	38,67	45,78
4.	39,67	51,89	65,61
5.	52,89	65,11	85,44
6.	66,11	78,33	105,28
7.	79,33	91,56	125,11
8.	92,56	104,78	144,94
9.	105,78	118,00	164,78
10.	119,00	131,22	184,61

The next step is to determine the Fuzzification value. The fuzzification process requires a membership function to obtain the degree of membership of a score weight in a set. As in the following Table 6.

Table 6. Weight Score

usage	Class	Fuzzification
99,43	1	A8
36,70	2	A6
27,38	3	A5
28,43	4	A5
28,43	5	A3
13,93	6	A6
34,46	7	A5
28,82	8	A5
16,09	9	A8
46,59	10	A3

Where to determine the fuzzification, namely the actual data plus the lower limit and upper limit values so that the fuzzification equals 99∪ 93 and 108 where∪ is a set so that the fuzzification is A8. The next step is the formation of Fuzzy Logic Relations (RLR). Based on the Ai value determined in the previous step where Ai is the month t and Aj is the month t+1 in the time series data which can be seen in the Table 7 below.

Table 7. Results of Fuzzy Logic Relations

No.	Fuzzyfics	Data Time Series	FLR
1.	A8	07 Jan –> 17 Jan	A8 –>A8
2.	A6	09 Jan –> 19 Jan	A6 –>A6
3.	A5	08 Jan –> 18 Jan	A4 –> A4
4.	A5	10 Jan –> 20 Jan	A5 –>A5
5.	A3	21 Jan –> 27 Jan	A2 –> A2
6.	A6	21 Feb–> 28 Feb	A6 –> A6
7.	A5	1 Mar –> 10 Mar	A5 –> A5
8.	A5	12 Mar –>16 Mar	A5 –> A5
9.	A8	20 Mar –> 27 Mar	A7 –> A7
10.	A3	24 Mar –> 28 Mar	A3 –>A3

The next step is to determine the Fuzzy Relations Group (FLRG) as shown in the following Table 8.

Table 8. FLRG results

Current State	Next State
A8	A8, A9
A6	A6, A7
A5	A5, A6

Current State	Next State
A3	A3, A4
A6	A6, A7
A5	A5, A6
A5	A5, A7
A8	A8, A9
A3	A3, A4

Where the process of forecasting and defuzzification is based on the FLRG that has been formed to facilitate the forecasting process for each actual existing data. The next step is to find the MAPE (Mean Absolute Percentage Error) value as shown in the following Table 9.

Table 9. Prediction Results

Transformer Power	predictions	Error Value	Absolute Value	MAP
100	10,69	5,69	0,057	0,57%
50	23,91	8,09	0,110	1,11%
50	64,08	2,08	0,037	0,38%
50	63,57	1,57	0,027	0,28%
50	44,56	15,44	0,551	5,52%
25	76,80	44,80	0,649	6,49%
50	90,02	28,02	0,483	4,83%
50	103,24	41,24	0,644	6,44%
50	116,46	111,46	1,198	11,99%
50	92,31	32,31	1,434	8,97%

The results of the usage load of transformer substations using the Avarage Based Times Series Method have an error rate of Mean Absolute Percentage Error (MAPE), which is an average of 11%. Specifically for the MAPE value, the error value is <100%. So that it can be said that the Avarage Based Fuzzy Times Series Method is very good to use for forecasting, especially for calculating the movement of load using transformer substations. Because it is able to produce forecasts with a very small degree of accuracy.

4. Conclusion

The results of the usage load of transformer substations based on transformer power consumption in 2020 at PT.PLN ULP (Persero) Krueng Geukuh are estimated to be an average of 75% and above with a transformer power capacity of 50 KVA and 100 KVA, which is significant for the yearly needs looking at the density of residents. The capacity is 50-150 KVA, so the transformer substation is at PT.PLN (Persero) ULP Krueng Geukuh in 2020 is estimated to have experienced an overload of 75% each month, not to mention the added density of buildings and residents, which can result in an unbalanced load with a resulting load that has been analyzed with the Average Based Times Series model with a MAPE level of an average of 11%. The test results of the system that has been designed are proven to be able to show the geographic location of a transformer power load that has been installed in every corner of the area properly. Forecasting is seen with a microscopic level of accuracy with a capacity of 50-150 KVA, which can result in an unbalanced load with population density.

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