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Fuzzy clustering means algorithm analysis for power demand prediction at PT PLN Lhokseumawe

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ABSTRACT

Indonesian National Electricity Company (PT PLN) as the main electric power provider in Lhokseumawe City. In fulfilling the need of electricity supply for the whole requirement, which upscale gradually. The proper forecasting method need to be premeditated. The area that was grouped based on the total of power consists of the four sub districts, namely Banda Sakti, Blang Mangat, Muara Dua and Muara Satu. In this study the fuzzy clustering mean (FCM) Classification was applied in determining the power demand of each area and categorized into a cluster respectively. The data clustering divided into six variable and five classifications of power of customer. Based on clustering step that applied revealed for four different classification of power requirement for future demand, the house hold electricity consumption measured for current consumption 9,588,466 Kw/H and forecast 10,037,248 Kw/H, for Business cluster classification measured 10,107,845 Kw/H and forecast 10,566,854 Kw/H, for industry the power measured 9,195,027 Kw/H and the forecasting revealed 9,638,804 Kw/H, and the last analysis was applied in general cluster classification based on measurement was recorded 9,729,048 Kw/H and forecasted result 10,198,282 Kw/H. this method has shown the better result in term of forecasting method by employing the cluster system in determining future power consumption requirement for the area of Lhokseumawe District.

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1. INTRODUCTION

Electricity demand is the crucial issue now days, the increasing of requirement growth tremendously along with the development of the era, generally every household, business customer and industries require different amount of power load, and for sure it has varies requirement of power consumption [1], [2]. To answer the problem that occurred many researchers have been conducting the research in predicting the requirement of power load [3], [4]. Different classification leads the researcher to find out the proper method in ensuring the power load demand of different area with different requirement [5]. Time series data of daily measurement record employed to train the prediction data which lead to the proper result of upcoming data in model of prediction [6].

In the current period, the various methods of time series forecasting have been applied in the electric load forecasting field [7]. Linear regression model using demand data to forecast the short-term peak load in a district-heating system [8], trigonometric grey prediction approach [9], concisely, artificial neural networks and support vector machines have a variety of applications in electric load forecasting [10]. Fuzzy logic [11], adaptive neuro fuzzy inference system [12], linear fuzzy regression [13], adaptive neuro fuzzy inference [14], [15], auto regressive integrated moving average [16]. However, the various method that have been applied to obtain the appropriate result in targeting the future demand of power load supply has each drawback [17].

Fuzzy clustering algorithms are mostly referred on splitting a set of data into divided clusters [18]. Various mathematical method, considered to classify the data [19]. To identify matches data concerning objects in the clusters [20], [21]. In this method, the data function is shown by regular alteration between zero and one. Consequently, indicates the method on how the object is categorized into different clusters. The FCM algorithm model can classify electrical power demands and competent to predict the number of new customer requests of each region which is shown from the customer data in each village and sub-district [22]. This will be useful for Indonesian National Electricity (PLN) in monitoring the supply of electric power so that the distribution of electrical energy remains stable and resourceful.

Through this study, the cluster method applied to identify electrical power clustering for each region in the working area of PLN which has variable value consisting of job (V1), overall income (V2), house area (V3), number of rooms (V4), number of equipment electronic (V5) and the amount of usage power (V6), each of which can be grouped into clustering classification to efficiently in predicting the power requirements of each sub-district or region grouping [23]. Furthermore, these variables were included in the process of FCM classification in determining the amount of power in each region and the system to be built in predicting the total amount of power installed from each grouping region.

2. RESEARCH METHOD

The proposed method that applied in this study is fuzzy logic, this method is applying mapping the spaces of an appropriate output space whereas, in fuzzy logic there are three processes that play a role, namely: fuzzification, inference, and defuzzification. furthermore the fuzzy cluster means (FCM) is a data grouping technique that is determined by the degree of membership [24]. The concept of fuzzy c-means is to determine the center of the cluster which will be a sign of the average location for each cluster. Cluster center will move forward to the optimal value by improving the cluster center and the membership value of each data repeatedly [25].

1) Initialize $U = [u_{ij}]$ matrix, $U^{(0)}$
2) At k-step: calculate the centers vectors $C^{(k)} = [c_j]$ with $U^{(\mathrm{k})}$

$$c_j = \frac{\sum_{i-1}^{N} u_{ij}^{m} . x_i}{\sum_{i-1}^{N} u_{ij}^{m}}$$

3) Update $U^{(\mathrm{k})}$ $U^{(\mathrm{k+1})}$

$$u_{ij} = \frac{1}{\sum_{k-1}^{c} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}}$$

4) If $|| U^{(\mathrm{k+1})} - U^{(\mathrm{k})} || < \sigma$ then STOP; otherwise return to step 2.

3. RESULTS AND ANALYSIS

The dense urban area has headed to the high demand for electricity in the city of Lhokseumawe which in 2020 is expected to increase to 15%. Based on the results of the prediction data, Indonesian National Electricity Company (PT PLN) Lhokseumawe must be able to reveal the patterns of grouping customer from each sub district in lhokseumawe area. In this study the Variable data that determines the demand of the electricity consist of six variable criteria of customer: V 1=occupation, V2=overall income, V3=spacious house, V4=number of rooms, V5 =the amount of electronic equipment, V 6=the amount of power consumption, the values of these variables will be grouped into four groups namely, C1=Subsidy R-1/450 VA, C2=Subsidy R-1/900 VA, C3=Non-Subsidy R-1/900, C4=Non-Subsidy R-1/1300. The initial step process of the FCM method is to determine the median of the cluster (centroid) arbitrarily, based on the Table 1 median cluster that can be determined, among others: C1=(2), C2=(9), C3=(4), C=(7).

Table 1. Customer data

Number	Customer's name	V1	V2	V3	V4	V5	V6
1	Terpiadi A. Majid	5	1	5	5	5	2
2	Sari yulis	1	5	2	1	1	4
3	Muharza	5	3	4	3	3	3
4	Muhammad Taib	5	1	5	5	5	1
5	Barmawi	2	3	3	3	3	2
6	Nazamuddin	2	5	3	3	3	4
7	Zulfikri	2	5	4	1	3	4
8	Edi Putra	2	1	3	3	3	4
9	Nora Kurnia Putri	2	3	3	1	3	3
10	Rahmat Shaleh	3	5	1	1	1	5

The first data gap (A) with the first cluster center:

$$PA_1 = \sqrt{(P_1A - P_1c_1)^2 + (P_2A - P_2c_1)^2 + (P_3A - P_3c_1)^2 + (P_4A - P_4c_1)^2 + (P_5A - P_5c_1)^2 + (P_6A - P_6c_1)^2}$$

$$= \sqrt{(5-2)^2 + (1-2)^2 + (5-2)^2 + (5-2)^2 + (5-2)^2 + (2-2)^2}$$

$$= 6.083$$

Second data gap (B) with the first cluster center:

$$PB_1 = \sqrt{(P_1B - P_1c_1)^2 + (P_2B - P_2c_1)^2 + (P_3B - P_3c_1)^2 + (P_4B - P_4c_1)^2 + (P_5B - P_5c_1)^2 + (P_6B - P_6c_1)^2}$$

$$= \sqrt{(1-2)^2 + (5-2)^2 + (2-2)^2 + (1-2)^2 + (1-2)^2 + (4-2)^2}$$

$$= 4.000$$

Third data gap (C) with the first cluster center:

$$PC_1 = \sqrt{(P_1C - P_1c_1)^2 + (P_2C - P_2c_1)^2 + (P_3C - P_3c_1)^2 + (P_4C - P_4c_1)^2 + (P_5C - P_5c_1)^2 + (P_6C - P_6c_1)^2}$$

$$= \sqrt{(5-2)^2 + (3-2)^2 + (4-2)^2 + (3-2)^2 + (3-2)^2 + (3-2)^2}$$

$$= 4.123$$

Fourth data gap (D) with the first cluster center:

$$PD_1 = \sqrt{(P_1D - P_1c_1)^2 + (P_2D - P_2c_1)^2 + (P_3D - P_3c_1)^2 + (P_4D - P_4c_1)^2 + (P_5D - P_5c_1)^2 + (P_6D - P_6c_1)^2}$$

$$= \sqrt{(5-2)^2 + (1-2)^2 + (5-2)^2 + (5-2)^2 + (5-2)^2 + (1-2)^2}$$

$$= 6.164$$

The time series data of power load consumption data present in the table are resulted from actual measurement that was conducted from different of power load within the area of Lhokseumawe, the result of cluster validity obtains used to determine optimum of targeting cluster. The calculation results between the initial data and the median showed the data result that associate to the cluster, which has the least gap from the median of the cluster. Furthermore, the stable data shown in Table 2 The median cluster of each datum for the average of the variable values included in a cluster in the results of the FCM classification.

The data present in Table 3 is the range data on second cluster, the data of power consumption classified into different cluster, which consist of three clusters namely C1, C2 and C3. The time series data which classified into three clusters of customers was calculated to obtain the appropriate power consumption demand among the customer in the area of Lhoskeumawe. The average data cluster in Table 4 tabulated from the overall total of measurement data of the first and the second cluster, the average data that presented as a convergence measure of a probability spread of defining variable of defining clusters.

Table 2. Clustering validity data of the first cluster

Num	Customer's name	Range C1	C2	C3	MIN	Cluster member
1	Terpiadi A. Majid	7.211102551	4.472135955	6	4.472135955	C2
2	Sari yulis	5.385164807	3	6.08276253	3	C2
3	Muharza	7.071067812	3.16227766	4.242640687	3.16227766	C2
4	Muhammad Taib	7.280109889	3.605551275	3	3	C1
5	Barmawi	5.830951895	3.16227766	5.830951895	3.16227766	C2
6	Nazamuddin	5.385164807	1	4.582575695	1	C1
7	Zulfikri	8.124038405	4.242640687	4.242640687	4.242640687	C3
8	Edi Putra	4	7.874007874	4.582575695	4	C2
9	Nora Kurnia Putri	2.236067977	8.306623863	4.242640687	2.236067977	C1
10	Rahmat Shaleh	3.464101615	6.32455532	7	3.464101615	C3

Table 3. Clustering validity data of the second cluster

Num	Customer's name	Range C1	C2	C3	MIN	Cluster member
1	Terpiadi A. Majid	7.874007874	7.692871993	8.484955006	7.692871993	C3
2	Sari yulis	8.306623863	9.373999144	4.821933508	4.821933508	C2
3	Muharza	6.32455532	6.153032732	7.641339196	6.153032732	C3
4	Muhammad Taib	8.326067471	7.570198961	3.782165436	3.782165436	C1
5	Barmawi	7.70407923	6.382092425	6.180334722	6.180334722	C1
6	Nazamuddin	8.27392238	7.74868493	8.778133358	7.74868493	C3
7	Zulfikri	8.595729895	7.166010349	5.108106818	5.108106818	C1
8	Edi Putra	7.538060373	8.859940582	7.166010349	7.166010349	C2
9	Nora Kurnia Putri	7.701805525	9.421260043	10.15502166	7.701805525	C2
10	Rahmat Shaleh	12.04292623	8.378320931	8.701142063	8.378320931	C1

Table 4. Average values of median cluster variable

	NEW CLUSTER 1					
Cluster	V1	V2	V3	V4	V5	V6
C1	3	3	3.666666667	3	3.666666667	2.666666667
C2	3	2.6	3.285714286	3	3	3
C3	2.5	5	2.5	1	2	4.5

3.1. Clustering validity data of cluster

The objective of clustering the data of customer is to determine the ordinary group of the data clusters; the algorithm was executed several times. Based on the number of clusters associated with the targeting variables, the maximum number of clusters, Therefore the iteration process was repeated for five times. The customer data that consist of, the customer's name, the name of the village, subdistrict of data center and cluster centroid, the following views are as follows: and cluster consisting of C1=Subsidy R-1/450 VA, C2=Subsidy R-1/900 VA, C3=Non-Subsidy R-1/900, C4=Non Subsidy R-1/1300, C5=Non Subsidy R-1/2200 VA.

The clustering validity data of power load consumption data presented in Table 5 was validating from data series of power load within the area of Lhokseumawe, the result of cluster validity obtains used to determine optimum of targeting cluster. The power load demand of customer varies broadly. The cluster validity and clustering phase employed to obtain a proper number of customer cluster, which is classified in targeting the validated propose of prediction of future consumption load of every group of customers.

3.2. Demand electric power requirements for each regional cluster

The data present in Figure 1 shown graph of cluster of customer demand of electric power for each customer group. The data of the electrical power requirements for each sub-district and the center of the cluster, for household customer the measured data were 9,588,446 and the prediction 10,037,248, business customer cluster the measured power of consumption were 10,107,845 and the prediction were 10,566,854, in industry cluster the measured power yield 9,195,022 and the prediction power yield 9,638,804, for the last cluster was grouped in general cluster the measure result were 9,729,048 and the prediction result yield 10,198,282.

Table 5. Clustering validity of customer data

Customer Name	Sub district	Area	Centroid 1	2	3	4	5	C1	C2	C3	C4	C5
Kamaruddin	Banda Sakti	Keude Aceh	6	4.472113 59549996	7.21110 2550928	5.47725S 750517	7.2111025 50928	0	1	0	0	0
Salamuddin Mureh	Banda Sakti	Keude Aceh	4.242640 6871193	3.162277 6601684	7.07106 78118655	4.89897948 55664	7.0710678 118655	0	1	0	0	0
Syambudiman IBR	Banda Sakti	Keude Aceh	6.4031242 374328	3.605551 275464	5.74456 2646538	4.1231056 256177	5.7445626 46538	0	1	0	0	0
Syarpiah Ibrahim	Banda Sakti	Keude Aceh	6.7823299 831253	2.449489 7427832	3.741657 3867739	2	3.7416573 867739	0	0	0	1	0
Nasai Adam	Banda Sakti	Kuta Blang	6	4.721359 549996	7.211102 550928	5.47722557 50517	7.2111025 50928	0	1	0	0	0
Hamdani	Banda Sakti	Pusong Baru	7	3.605551 275464	5	3.60555127 5464	5	0	1	0	0	0
Yusuf Karim	Banda Sakti	Pusong Baru	7.3484692 283495	3.741657 3867739	4.690415 7598234	3.46410161 51378	4.6904157 598234	0	1	0	0	0
Anwar Ismail	Banda Sakti	Pusong Baru	5.9160797 830996	2.645751 3110646	5.196152 4227066	3.31662479 03554	5.1961524 227066	0	1	0	0	0
A. Bakar Ben	Banda Sakti	Pusong Baru	5.7445626 46538	3.605551 275464	6.403124 2374328	4.58257569 49558	6.4031242 374328	0	1	0	0	0
Zakaria	Banda Sakti	Pusong Lama	6.4807406 984079	3.162277 6601684	5.099019 5135928	3.46410161 51378	5.0990195 135928	0	1	0	0	0
M.Jafar Daud	Banda Sakti	Pusong Lama	5.2915026 221292	3.464101 6151378	6.633249 5807108	4.69041575 98234	6.6332495 807108	0	1	0	0	0
Hj. Nurdin BR Bangun	Banda Sakti	Pusong Lama	5.8309518 948453	3.162277 6601684	5.830051 8948453	4	5.8300518 948453	0	1	0	0	0
Marzuki Rahman	Banda Sakti	Pusong Lama	7.1414284 285429	3.872983 3462074	5.196152 4227066	3.87298334 62074	5.1961524 227066	0	1	0	0	0
Said Husaini	Banda Sakti	Pusong Lama	7.0710678 118655	3.162277 6601684	4.242640 6871193	2.82842712 47462	4.2426406 871193	0	1	0	0	0
Mukhtar S	Blang Mangat	Alue Lim	7	3.605551 275464	5	3.60555127 5464	5	0	0	0	1	0
Zakaria Sulaiman	Blang Mangat	Alue Lim	6.6332495 807108	34641016 151378	5.291502 6221292	3.74165738 67739	5.2915026 221292	0	1	0	0	0
Ilyas Harun	Blang Mangat	Alue Lim	4.7958315 233127	1.732050 8075689	5.567764 36283	3.3166247 903554	5.567764 36283	0	1	0	0	0
Ibrahim TB	Blang Mangat	Alue Lim	4.7958315 233127	3.316624 7903554	6.855654 600401	4.7958315 233127	6.855654 600401	0	1	0	0	0
Ismail Benseh	Blang Mangat	Alue Lim	4.2426406 871193	3.162277 6601684	7.071067 8118655	4.89897948 55664	7.07106781 18655	0	1	0	0	0

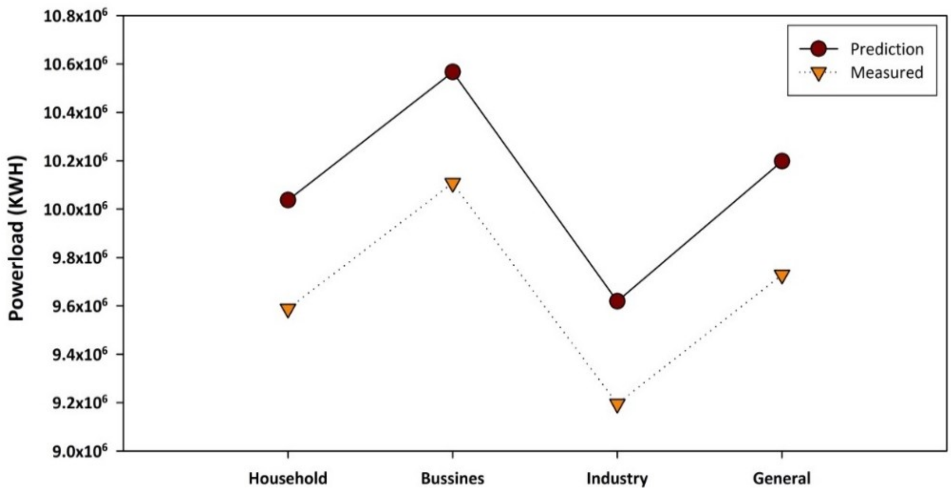

Figure 1. Electricity demands in each cluster of sub district in Lhokseumawe

4. CONCLUSION

Fuzzy Clustering Means Algorithm Analysis method has revealed the result of forecasting method by employing the cluster system in determining the future power consumption requirement, for the area of Lhokseumawe District. The data series that obtain from regular measurement that employed was divided into cluster by using the cluster validity method therefore the FCM method to obtain an appropriate forecasting of power load. This method has shown the reliability of forecasting method that provides the predicting demand of electric power of customer in Lhokseumawe district.

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