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Electricity Demand Forecasting by Using Modified Fuzzy Logic

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Abstract: This study aims to forecast long-term electrical energy demand in Banten Province in 2020-2030 using modified fuzzy logic as an effort to ensure a balance between demand and supply of electrical energy and reduce the risk of an energy crisis in the future as a result of economic growth and development. rapid population. The modification made in this study lies in the way of forming fuzzy rules based on historical electricity data for 2010-2019, so that fuzzy logic has fewer rules and is more effective. In this study, it was found that modified fuzzy logic has a good forecasting ability with an average error of 13,63% and 17,04%, respectively on the historical data of 2010-2019 and the actual data of 2020 and also have an average accuracy of 97,22% for the overall forecast and 97,01% for the combined sectoral forecast against RUPTL.

Keywords: fuzzy logic, energy forecasting, fuzzy rules, fuzzy modification

INTRODUCTION

(Torrini *et al.*, 2016) to forecast the demand for electrical energy in Brazil and resulted in an error of 1,46%. Therefore, the approach using fuzzy logic is a suitable method to be used in this research. This research was conducted with the aim of implementing modified fuzzy logic as a method of forecasting electrical energy demand in Banten Province from 2020 to 2030 and to determine the level of accuracy of the modified fuzzy logic method for forecasting electricity demand.

Modification of fuzzy logic is an attempt to show the flexibility of fuzzy logic, but it is also intended to optimize the use of fuzzy logic to solve a problem (Wardoyo & Yuniarti, 2020). According to (Wardoyo & Yuniarti, 2020), modifications to fuzzy logic can be done by modifying some stages of the fuzzy logic process consisting of fuzzification, fuzzy inference, and fuzzy rule base. Even so, modifications can also be made by adding other methods such as clustering into the fuzzy logic process (Jain *et al.*, 2020). Another study that made modifications only to the rule base of fuzzy logic was carried out by (Maspiyanti *et al.*, 2013) by reducing the amount of the rules used to produce more effective results and (Azimjonov *et al.*, 2016), by adding additional rules to increase the accuracy of the results.

METHODS

The forecast model that will be made in this study is a model for forecasting electrical energy needs based on economic variables and population growth and also the number of electricity customers using the fuzzy logic method. The results of this study are the overall and sectoral profile of the Banten Province's electrical energy needs from 2020-2030 which are described annually. There are two types of forecasts that will be made, namely, forecasts for each PLN's customer sector and overall energy demand forecasts in the Banten Province from 2020 to 2030. Each forecast is made with two different sets of fuzzy rules, namely, the unmodified rules and modified rules. This is done to compare the success rate of modified fuzzy logic to unmodified fuzzy logic.

This research consists of three stages, namely, historical data processing using quadratic trend analysis, creating fuzzy membership functions, forming fuzzy rules, and fuzzy logic designer which illustrated by Fig-1.

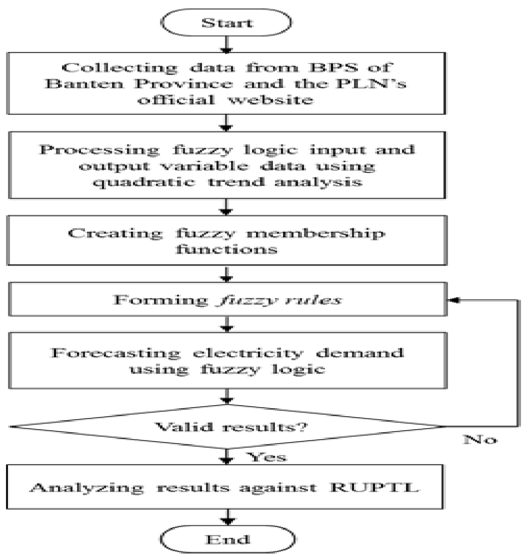

Fig-1. Research Flowchart

The data used in this study are historical data on electricity, population, and the Gross Regional Domestic Product (GRDP) of Banten Province in 2010-2019 which were obtained from the BPS and the Business Plan for the Provision of Electricity for 2019-

2028 (RUPTL – Rencana Usaha Penyediaan Tenaga Listrik). The data that has been obtained then processed using the quadratic trend analysis method to form input and output values as well as the universe of discourse for each type of fuzzy logic forecast. After that, the design of membership functions and the formation of fuzzy logic rules for each forecast is carried out based on the results of the quadratic trend analysis of each forecast model. The validation of the forecast results by sector and overall forecast is carried out on the actual and historical data that has been collected. Validation is carried out using Mean Absolute Percentage Error (MAPE) analysis to determine the feasibility or reliability of this forecast model for forecasting. After that, the results of the unmodified and modified fuzzy logic forecasts are compared to the accuracy of PLN's forecast data, which is RUPTL. The equation used to calculate the MAPE is shown by (1) (Vivas *et al.*, 2020).

$$MAPE = \left(\frac{100}{n}\right)\sum_{t=1}^{n}\frac{|x_t - f_t|}{x_t} \text{ ....(1)}$$

Where x_t is historical data in period t, f_t is forecast value in period t, and n is number of forecast data.

Processing of Input and Output Variables Using Quadratic Trend Analysis

Determination of the value of input and output variables is carried out to determine the value to be entered into the fuzzy logic process for overall and sectoral forecasts, form modified fuzzy logic rules, and also aims to determine the value of the universe of discourse. To determine the value of the universe of discourse, each variable needs to know its minimum and maximum values. The variables used in this study are the population, the number of sectoral electricity customers, GRDP, and the need for electrical energy. The method used to obtain input values from overall and sectoral forecasts for 2020-2030 is the quadratic trend method analysis. Trend values are obtained by entering historical data from each variable into (2) to (5), where Y' is the estimated value of the x-th period, a is a constant, b is a first coefficient, c is a second coefficient, X is a period, and Y is a historical data value (Purwanto & Suharyadi, 2016).

$$Y' = a + bX + cX^2 \text{ ....(2)}$$

$$a = \frac{\Sigma Y(\Sigma X^4) - (\Sigma X^2 Y)(\Sigma X^2)}{n(\Sigma X^4) - (\Sigma X^2)^2} \text{ ....(3)}$$

$$b = \frac{\Sigma XY}{\Sigma X^2} \text{ ....(4)}$$

$$c = \frac{n(\Sigma X^2 Y) - (\Sigma X^2)(\Sigma Y)}{n(\Sigma X^4) - (\Sigma X^2)^2} \text{ ....(5)}$$

The results of the quadratic trend of each variable for the overall and sectoral forecasts are then combined with the historical data to form the input values of the overall and sectoral forecasts for 2010 to 2030. The input and output values for each forecast are shown in Tables 1 to Table 5. In Tables 1 to Table 5, all values from 2010-2019 are historical data on electricity for Banten Province taken from (BPS Provinsi Banten, 2021; PT. Perusahaan Listrik Negara, 2019). Meanwhile, all values from 2020-2030 in Table-1 to Table 5 are the result values of the quadratic trend.

Table-1: I/O Values for Overall Forecast

Year	Population	GRDP (IDR)	Demand (MWh)
2010	10.632.166	271.465.283	16.293.265
2011	11.005.518	290.545.839	17.682.052
2012	11.248.947	310.385.592	18.890.594
2013	11.452.491	331.099.106	19.247.000
2014	11.704.877	349.584.668	19.210.000
2015	11.955.243	369.209.288	18.641.174
2016	12.203.148	389.543.932	20.368.564
2017	12.448.160	412.639.618	21.681.470
2018	12.689.736	437.676.191	23.161.851
2019	12.927.316	461.906.047	23.547.000
2020	13.186.480	486.424.432	25.296.916
2021	13.439.367	512.427.975	26.903.050
2022	13.694.296	539.309.881	28.673.023
2023	13.951.267	567.070.150	30.606.835
2024	14.210.281	595.708.781	32.704.487
2025	14.471.338	625.225.775	34.965.978
2026	14.734.437	655.621.131	37.391.308
2027	14.999.579	686.894.850	39.980.477
2028	15.266.763	719.046.932	42.733.486
2029	15.535.990	752.077.376	45.650.334
2030	15.807.259	785.986.183	48.731.021

The universe of discourse values of each variable for the overall forecast can be determined by rounding to the nearest of the lowest and highest values of each variable. To facilitate the process of entering data into the fuzzy logic designer, it is necessary to dividing it by one million. The universe of discourse for the population, grdp, and demand variable respectively are, 10,5 to 16; 270 to 786; and 16 to 49. From Table-2 to Table 5 is done in the same way.

Table-2: I/O for Household Sector

Year	Number of Customer	GRDP (IDR)	Demand (MWh)
2010	1.769.436	271.465.283	3.411.916
2011	1.856.615	290.545.839	3.680.989
2012	2.006.912	310.385.592	4.050.305
2013	1.991.900	331.099.106	3.640.000
2014	2.177.500	349.584.668	3.982.000
2015	2.760.359	369.209.288	4.370.277
2016	2.547.847	389.543.932	4.543.270
2017	2.711.966	412.639.618	4.599.679
2018	2.893.899	437.676.191	4.825.167
2019	3.077.930	461.906.047	5.231.000
2020	3.213.128	486.424.432	5.507.948
2021	3.360.787	512.427.975	5.851.029
2022	3.506.939	539.309.881	6.223.139
2023	3.651.584	567.070.150	6.624.278
2024	3.794.722	595.708.781	7.054.446
2025	3.936.354	625.225.775	7.513.643
2026	4.076.479	655.621.131	8.001.869
2027	4.215.098	686.894.850	8.519.125
2028	4.352.210	719.046.932	9.065.409
2029	4.487.815	752.077.376	9.640.723
2030	4.621.914	785.986.183	10.245.065

Table-3: I/O Values for Industrial Sector

Year	Number of Customer	GRDP (IDR)	Demand (MWh)
2010	6.174	271.465.283	10.962.941
2011	6.453	290.545.839	11.471.663
2012	6.735	310.385.592	12.353.842
2013	5.600	331.099.106	12.920.000
2014	5.700	349.584.668	12.569.000
2015	6.326	369.209.288	11.645.063
2016	6.125	389.543.932	12.810.736
2017	6.324	412.639.618	13.623.275
2018	6.497	437.676.191	14.803.301
2019	6.698	461.906.047	14.601.000
2020	7.204	486.424.432	15.632.114
2021	7.691	512.427.975	16.507.724
2022	8.260	539.309.881	17.477.341
2023	8.911	567.070.150	18.540.967
2024	9.644	595.708.781	19.698.600
2025	10.459	625.225.775	20.950.240
2026	11.357	655.621.131	22.295.889
2027	12.336	686.894.850	23.735.545
2028	13.398	719.046.932	25.269.209
2029	14.541	752.077.376	26.896.881
2030	15.767	785.986.183	28.618.561

Table-4: I/O Values for Business Sector

Year	Number of Customer	GRDP (IDR)	Demand (MWh)
2010	82.735	271.465.283	1.510.230

2011	87.808	290.545.839	1.930.876
2012	98.445	310.385.592	1.789.886
2013	93.000	331.099.106	2.299.000
2014	100.500	349.584.668	2.243.000
2015	128.433	369.209.288	2.147.564
2016	131.067	389.543.932	2.343.616
2017	150.570	412.639.618	2.520.949
2018	171.377	437.676.191	2.736.677
2019	175.019	461.906.047	2.930.000
2020	201.447	486.424.432	3.106.780
2021	222.789	512.427.975	3.328.697
2022	245.850	539.309.881	3.568.596
2023	270.630	567.070.150	3.826.475
2024	297.128	595.708.781	4.102.334
2025	325.345	625.225.775	4.396.175
2026	355.281	655.621.131	4.707.996
2027	386.935	686.894.850	5.037.798
2028	420.308	719.046.932	5.385.581
2029	455.400	752.077.376	5.751.345
2030	492.211	785.986.183	6.135.090

Table-5: I/O Values for Public Sector

Year	Number of Customer	GRDP (IDR)	Demand (MWh)
2010	42.062	271.465.283	408.178
2011	45.600	290.545.839	598.524
2012	49.348	310.385.592	696.561
2013	44.700	331.099.106	388.000
2014	47.500	349.584.668	416.000
2015	59.793	369.209.288	478.270
2016	56.974	389.543.932	670.941
2017	63.721	412.639.618	937.567
2018	70.742	437.676.191	796.706
2019	76.095	461.906.047	785.000
2020	84.748	486.424.432	1.050.074
2021	93.509	512.427.975	1.215.600
2022	103.156	539.309.881	1.403.948
2023	113.687	567.070.150	1.615.117
2024	125.103	595.708.781	1.849.108
2025	137.403	625.225.775	2.105.921
2026	150.589	655.621.131	2.385.555
2027	164.659	686.894.850	2.688.011
2028	179.615	719.046.932	3.013.289
2029	195.455	752.077.376	3.361.388
2030	212.180	785.986.183	3.732.309

Creating Fuzzy Membership Functions

The membership function for each unmodified and modified fuzzy logic forecast is the same. Each variable consists of 7 fuzzy sets and all of them are triangular functions. The membership function tables for the overall forecast, household, industrial, business, and general sectors are shown in Table 6 to Table-10, where F is the function (input/output), Var is Variable, FS is fuzzy set, UD is the universe of discourse, and the domain is the location of the fuzzy set in the universe of discourse. In the overall forecast, the input variable used is the population and GRDP and the output variable is energy demand, while in the sectoral forecast, the output variable is still the same, namely sectoral energy demand, while the input variables are the number of customers and GRDP.

Table-6:Overall Forecast Membership Function

F	Var	FS	UD	Domain
In	Pop.	A1	10.5 - 16	[9.587; 10.5; 11.41]
		A2		[10.5; 11.41; 12.34]

		A3		[11.41; 12.34; 13.25]
		A4		[12.34; 13.25; 14.16]
		A5		[13.25; 14.16; 15.09]
		A6		[14.16; 15.09; 16]
		A7		[15.09; 16; 16.92]
In	GRDP	B1	270 - 786	[184; 270; 356]
		B2		[270; 356; 442]
		B3		[356; 442; 528]
		B4		[442; 528; 614]
		B5		[528; 614; 700]
		B6		[614; 700; 786]
		B7		[700; 786; 872.1]
F	**Var**	**FS**	**UD**	**Domain**
Out	Demand	C1	16 - 49	[10.5; 16; 21.5]
		C2		[16; 21.5; 27]
		C3		[21.5; 27; 32.5]
		C4		[27; 32.5; 38]
		C5		[32.5; 38; 43.5]
		C6		[38; 43.5; 49]
		C7		[43.5; 49; 54.51]

Table-7: Household Sector Membership Function

F	Var	FS	UD	Domain
In	Num. Cost.	A1	1.5 – 5	[0.919; 1.5; 2.079]
		A2		[1.5; 2.079; 2.671]
		A3		[2.079; 2.671; 3.25]
		A4		[2.671; 3.25; 3.829]
		A5		[3.25; 3.829; 4.421]
		A6		[3.829; 4.421; 5]
		A7		[4.421; 5; 5.585]
In	GRDP	B1	270 – 786	[184; 270; 356]
		B2		[270; 356; 442]
		B3		[356; 442; 528]
		B4		[442; 528; 614]
		B5		[528; 614; 700]
		B6		[614; 700; 786]
		B7		[700; 786; 872.1]
Out	Demand	C1	3 – 10.5	[1.75; 3; 4.25]
		C2		[3; 4.25; 5.5]
		C3		[4.25; 5.5; 6.75]
		C4		[5.5; 6.75; 8]
		C5		[6.75; 8; 9.25]
		C6		[8; 9.25; 10.5]
		C7		[9.25; 10.5; 11.75]

Table-8: Industrial Sector Membership Function

F	Var	FS	UD	Domain
In	Num. Cost.	A1	0.0055 – 0.016	[0.003757; 0.0055; 0.007238]
		A2		[0.0055; 0.007238; 0.009012]
		A3		[0.007238; 0.009012; 0.01075]
		A4		[0.009012; 0.01075; 0.01248]
		A5		[0.01075; 0.01248; 0.01427]
		A6		[0.01248; 0.01427; 0.016]
		A7		[0.01427; 0.016; 0.01775]
In	GRDP	B1	270 – 786	[184; 270; 356]
		B2		[270; 356; 442]
		B3		[356; 442; 528]

		B4		[442; 528; 614]
		B5		[528; 614; 700]
		B6		[614; 700; 786]
		B7		[700; 786; 872.1]
Out	Demand	C1	10.5 – 29	[7.417; 10.5; 13.58]
		C2		[10.5; 13.58; 16.67]
		C3		[13.58; 16.67; 19.75]
		C4		[16.67; 19.75; 22.83]
		C5		[19.75; 22.83; 25.92]
		C6		[22.83; 25.92; 29]
		C7		[25.92; 29; 32.09]

Table-9: Business Sector Membership Function

F	Var	FS	UD	Domain
In	Num. Cost.	A1	0.08 – 0.5	[0.01028; 0.08; 0.1495]
		A2		[0.08; 0.1495; 0.2205]
		A3		[0.1495; 0.2205; 0.29]
		A4		[0.2205; 0.29; 0.3595]
		A5		[0.29; 0.3595; 0.4305]
		A6		[0.3595; 0.4305; 0.5]
		A7		[0.4305; 0.5; 0.5703]
In	GRDP	B1	270 – 786	[184; 270; 356]
		B2		[270; 356; 442]
		B3		[356; 442; 528]
		B4		[442; 528; 614]
		B5		[528; 614; 700]
		B6		[614; 700; 786]
		B7		[700; 786; 872.1]
Out	Demand	C1	1.5 – 6.5	[0.6667; 1.5; 2.333]
		C2		[1.5; 2.333; 3.167]
		C3		[2.333; 3.167; 4]
		C4		[3.167; 4; 4.833]
		C5		[4; 4.833; 5.667]
		C6		[4.833; 5.667; 6.5]
		C7		[5.667; 6.5; 7.335]

Table-10: Public Sector Membership Function

F	Var	FS	UD	Domain
In	Num. Cost.	A1	0.042 – 0.2125	[0.0137; 0.042; 0.07021]
		A2		[0.042; 0.07021; 0.09904]
		A3		[0.07021; 0.09904; 0.1272]
		A4		[0.099; 0.127; 0.156]
		A5		[0.1272; 0.1555; 0.1843]
		A6		[0.1555; 0.1843; 0.2125]
		A7		[0.1843; 0.2125; 0.241]
In	GRDP	B1	270 – 786	[184; 270; 356]
		B2		[270; 356; 442]
		B3		[356; 442; 528]
		B4		[442; 528; 614]
		B5		[528; 614; 700]
		B6		[614; 700; 786]
		B7		[700; 786; 872.1]
Out	Demand	C1	0.35 – 4	[-0.2583; 0.35; 0.9577]
		C2		[0.35; 0.9577; 1.567]
		C3		[0.9577; 1.567; 2.175]
		C4		[1.567; 2.175; 2.783]
		C5		[2.175; 2.783; 3.392]

		C6		[2.783; 3.392; 4]
		C7		[3.392; 4; 4.61]

Forming Fuzzy Rules

The rules for unmodified fuzzy logic are the same for either sectoral or overall forecasts as shown in Table-11. The rules are made by combining all the possibilities. Because there are 7 fuzzy sets in each membership function, a total of 49 rules are formed with two input variables and an output variable. A and B are input variables and C are output variables. The rules in Table 11 are applied to the unmodified forecast to the overall and sectoral forecasts, which are the household, industrial, business and public sectors.

Table-11:Unmodified Fuzzy Rules

	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**
B1	C1	C1	C2	C2	C3	C4	C5
B2	C1	C2	C3	C3	C4	C4	C5
B3	C2	C3	C3	C4	C4	C5	C6
B4	C2	C3	C4	C4	C5	C5	C6
B5	C3	C4	C4	C5	C5	C6	C6
B6	C4	C4	C5	C5	C6	C6	C7
B7	C5	C5	C6	C6	C6	C7	C7

The rules for modified fuzzy logic are formed based on the relationship between input and output in the membership function that has been created. Each type of modified forecast has different rules to adjust the relationship of each variable to the forecast itself. How to create rules for overall forecasts is exemplified as follows:

- The year 2010
  pupulation = 10.632.166 people
  GRDP = IDR 271.465.283
  Electricity Demand = 16.293.265 MWh

Referring to Table-6, the above data is divided into certain fuzzy sets for each variable. The population in 2010 lies in the fuzzy set A1 and A2. GRDP in 2010 lies in fuzzy sets B1 and B2. The demand for electrical energy in 2010 lies in the fuzzy sets C1 and C2. Based on this, the rules formed are as follows:

- *If (population is A1) and (grdp is B1) Then (demand is C1)*
- *If (population is A2) and (grdp is B2) Then (demand is C2)*
- The year 2016
  pupulation = 12.203.148 people
  GRDP = IDR 271.465.283
  Electricity Demand = 16.293.265 MWh

By looking at Table-6, the population in 2016 lies in the fuzzy set A2 and A3. GRDP in 2016 lies in fuzzy sets B2 and B3. The demand for electrical energy in 2016 lies in the fuzzy set C1 and C2. Based on this, the rules formed are as follows:

- *If (population is A2) and (grdp is B2) Then (demand is C1)*
- *If (population is A3) and (grdp is B3) Then (demand is C2)*

The above method is used for other years and also applies to sectoral forecasts. If formed into a table, the rules for the overall forecast, household, industrial, business, and public sectors can be seen in Tables 12 to Table 16. Forming rules like this will result in fewer rules. In addition, in the modified fuzzy rules, the rules that are formed from the combination of an antecedent can have a number of consequences as much as one or two consequences. This is because the formation of rules is based on the input and output values of the historical data and quadratic trend analysis, so that every year that will be forecasted has its own rules.

Table-12: Overall Forecast Modified Rules

	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**
B1	C1	C1	-	-	-	-	-
B2	-	C1, C2	C2	-	-	-	-
B3	-	-	C2	C2, C3	-	-	-
B4	-	-	-	C3	C3, C4	-	-
B5	-	-	-	-	C4, C5	C5	-
B6	-	-	-	-	-	C5, C6	-
B7	-	-	-	-	-	-	C6, C7

Table-13: Household Sector Modified Rules

	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**

B1	C1	C1		-	-	-	-
B2	-	C2	C2	-	-	-	-
B3	-	-	C3	C3	-	-	-
B4	-	-	-	C3, C4	C4	-	-
B5	-	-	-	-	C4, C5	-	-
B6	-	-	-	-	C5	C5, C6	-
B7	-	-	-	-	-	C6	C7

Table-14: Industrial Sector Modified Rules

	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**
B1	C1	-	-	-	-	-	-
B2	C1, C2	C2	-	-	-	-	-
B3	C2	C2, C3	-	-	-	-	-
B4	-	C3	C3	-	-	-	-
B5	-	-	C4	C4	-	-	-
B6	-	-	-	C5	C5	C6	-
B7	-	-	-	-	C6	C6	C7

Table-15: Business Sector Modified Rules

	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**
B1	C1	-	-	-	-	-	-
B2	C1, C2	C2	-	-	-	-	-
B3	-	C2, C3	C3	-	-	-	-
B4	-	-	C3	C4	-	-	-
B5	-	-	-	C4	C5	-	-
B6	-	-	-	-	C5	C6	-
B7	-	-	-	-	-	C6	C7

Table-16: Public Sector Modified Rules

	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**
B1	C1	-	-	-	-	-	-
B2	C1	C1, C2	-	-	-	-	-
B3	-	C1, C2	C2	-	-	-	-
B4	-	-	C2, C3	-	-	-	-
B5	-	-	-	C3, C4	-	-	-
B6	-	-	-	-	C4, C5	C5, C6	-
B7	-	-	-	-	-	C5, C6	C6, C7

Designing Fuzzy Logic Designer

The process after creating the membership function and fuzzy rules is designing the Fuzzy Logic Designer. The steps in designing Fuzzy Logic Designer for overall and sectoral are as follows:

- After opening the Fuzzy Logic Designer, then creating a fuzzy system with 2 inputs and 1 output. Then entering the value of the universe of discourse and the domain of the membership function of the fuzzy set of each variable according to the membership function table that has been created. In Fig-2(a), the membership function for the population variable of the overall forecast is shown.
- Inserting fuzzy rules, in this case exemplified by the overall modified fuzzy logic forecast, so inserting modified fuzzy rules into Fuzzy Logic Designer by choosing "*Edit*" > "Rules" in the toolbar.
- Opening the rule viewer to get the forecast results by entering the values of the input variables from the forecast input-output table, Table-1 to Table-5. The rule viewer is shown in Fig-2(b).

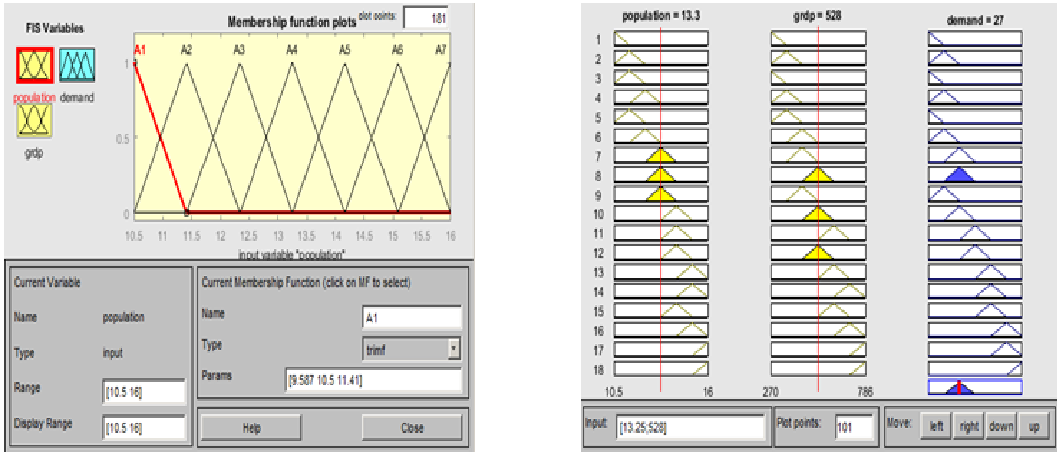

Fig-2: Matlab Fuzzy Logic Desginer (a) Membership Fungctions Editor and (b) Rule Viewer

RESULTS AND DISCUSSION

The energy forecast results are obtained after the process of entering the input data into fuzzy logic desginer is complete. The forecast results are presented in two categories, namely the overall forecast results and the sectoral forecasts for PLN's customers from 2010 to 2030.

Overall Forecast Results

The overall forecast results are shown in Fig-2. As can be seen from Fig-2, the results of the unmodified forecast have a graph that tends to be linear. In addition, the growth in electricity demand from year to year is seen to grow in the same amount. On the other hand, the results of the modified forecast have a more dynamic graphic form, so that the production of electrical energy each year can vary according to more real economic and population conditions. This will make electrical energy planning better and reduce the cost of electricity generation.

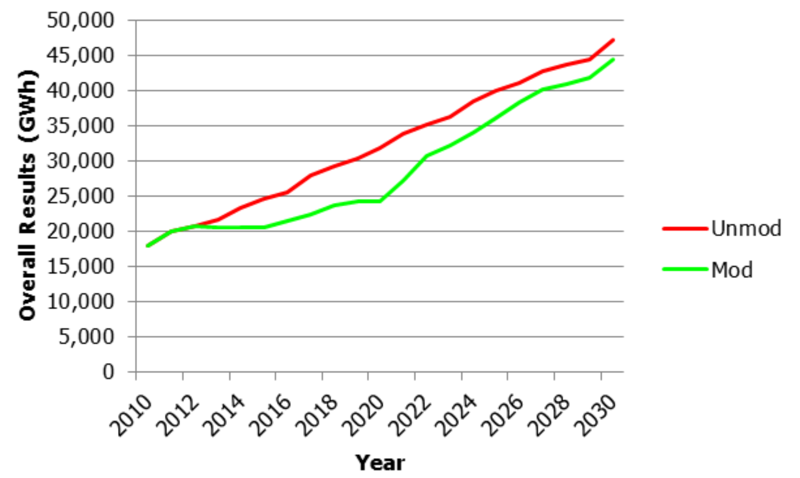

Fig-2: Comparison Graph of Modified Fuzzy Logic Overall Forecasts Against Unmodified Forecasts

Sectoral Forecast Results

The sectoral forecast results are shown in Fig-3. Fig-3 shows a comparison of unmodified and modified sectoral forecast results. Based on Fig-3, in general, the forecast results using modified fuzzy logic have lower results than the unmodified forecast results. In addition, it is particularly evident that the industrial sector is the sector with the highest demand for electrical energy among other sectors. The PLN's customer sector with the largest demand for electrical energy after the industrial sector, respectively, is the household, business and public sectors.

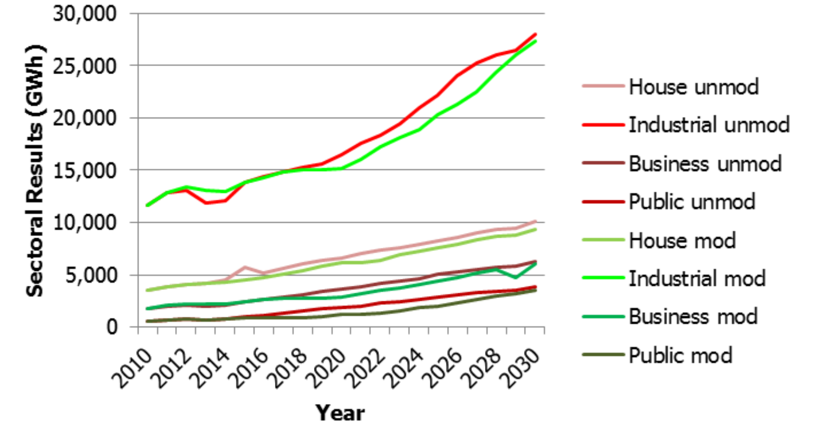

Fig-3. Comparison Graph of Modified Fuzzy Logic Sectoral Forecast Against Unmodified Forecast

Forecast Validation

The accuracy of a forecast model is very important because it plays a role in determining the reliability of the forecast model. Validation is carried out to determine whether the model is reliable or not to make forecasts. The forecast result is very good if it has a MAPE value less than 10% and has a good ability if the average error value is less than 20% (Ding *et al.*, 2018). Validation is done by comparing the forecast data with historical data from 2010 to 2019. The MAPE value for each type forecast is shown in Table-17.

Table-17:MAPE Value of Forecast Result Against 2010-2019 Data

Forecast Type	MAPE (%)	
	Fuzzy Unmodified	Fuzzy Modified
Overall	20,87	7,14
Household Sector	15,03	7,15
Industrial Sector	8,7	7,67
Business Sector	1,7	9,67
Public Sector	6,21	36,50
Average	**24,43**	**13,63**

Based on Table-17, it is known that the MAPE value of historical data produced by unmodified fuzzy logic on average from all forecasts is 24,43%, while the modified fuzzy logic MAPE has an average of 13,63%. This indicates that the modified fuzzy logic has good forecasting ability on historical data because the MAPE value is less than 20%. Even if viewed in more detail, each modified fuzzy logic forecast has a very good forecasting ability with a MAPE value less than 10%, except for public sector forecasts where the MAPE value is more than 20%. Based on (Ding *et al.*, 2018), the MAPE value of 36,50% is still acceptable, while the MAPE value above 50% is declared inappropriate. Even so, the modified fuzzy logic was able to improve the MAPE value of the public sector to be better from 65,21% to 36,50%. In addition, the validation of the forecast results against the actual data is carried out by comparing the overall and sectoral forecast results with the actual data in 2020 taken from Banten Province in Figures 2021 as can be seen in Table 18. Based on Table 18, average error value obtained for the modified fuzzy forecast is 17,04% and 50,02% with unmodified fuzzy forecast.

Table-18: 2020 Forecast Results against 2020 Actual Data

Forecast Type	Fuzzy Forecast (GWh)		2020 Actual Data (GWh)	Error (%)	
	Fuzzy Unmodified	Fuzzy Modified		Fuzzy Unmodified	Fuzzy Modified
Overall	31.800	24.300	22.352	42,27	8,72
Household Sector	6.610	6.130	5.871	12,59	4,41
Industrial Sector	16.500	15.200	13.027	26,66	16,68
Business Sector	3.590	2.870	2.651	35,42	8,26
Public Sector	1.870	1.180	802	133,17	47,13
Average				**50,02**	**17,04**

Comparison of Overall Forecast Results against RUPTL

The overall forecast results of unmodified and modified fuzzy logic are compared with the estimated electricity demand data from RUPTL. The results comparison of overall forecasts against RUPTL are shown in Figure 4.

The RUPTL used as a validator in this study only provides an overview of the electrical energy demands of Banten Province until 2028 because at the time of this study done, PLN has not issued RUPTL for forecasts until 2030, so the error rate and accuracy of forecast results in 2029 and 2030 are not yet known.

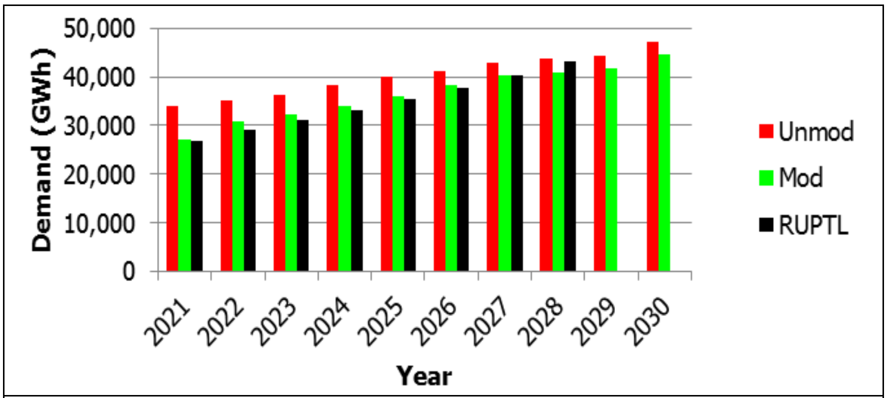

Fig-4: Comparison of Overall Forecast Against RUPTL

Fig-4 shows a comparison graph between the forecast results with unmodified and modified fuzzy logic against RUPTL. Based on Fig-4, the results of the modified fuzzy logic forecast are closer to the RUPTL value. Therefore, the level of accuracy of forecasts using modified fuzzy logic are generally better than those of unmodified fuzzy logic forecasts. Comparison of the average accuracy of these two can be seen in Fig-5.

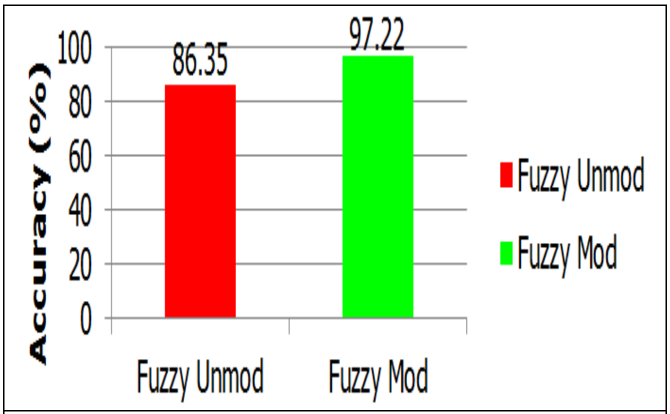

Fig-5: Comparison of Overall Accuracy Against RUPTL

Based on Fig-5, the modified forecast produces an accuracy of up to 97,22% compared to the unmodified forecast which is only 86,35%. With these results, the modified fuzzy logic increases the overall forecast accuracy up to 10,87% against RUPTL.

Comparison of Sectoral Forecast against RUPTL

Another comparison made for the sectoral forecasts. The comparison is done by summing the forecast results of each sector to become the combined result of all sector from a single year. This is happened because the electrical energy generation carried out by PLN is based on the need for electrical energy in general and does not generate electrical energy for a number of specific sector demands. The results of the comparison are shown in Fig-6.

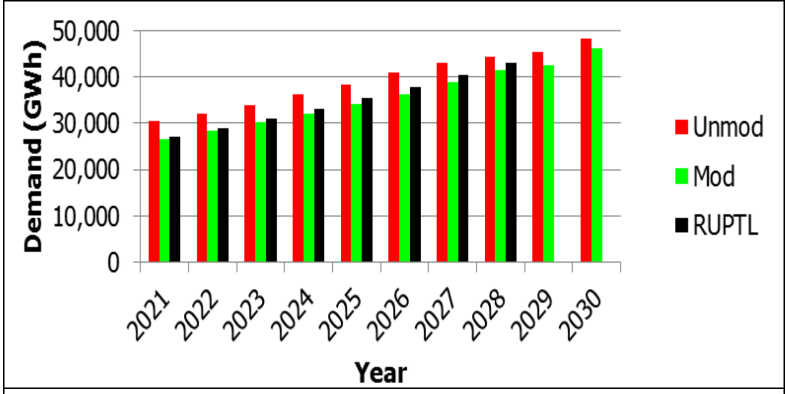

Fig-6:Comparison of Sectoral Forecast Against RUPTL

Fig-6 shows a graph of the comparison between the combined results of sectoral forecasts of unmodified and modified fuzzy logic against the RUPTL. Based on Fig-6, the graph of the modified fuzzy logic forecast appears to have a closer results to the graph of the RUPTL. This closer result causes the error rate and accuracy of forecasts using modified fuzzy logic in general to be better than those of unmodified fuzzy logic forecasts. This implies that, forecasting using modified fuzzy logic for forecasting electrical energy demand in Banten Province by sector produces better results than the unmodified fuzzy logic forecast results. Comparison of the average accuracy of fuzzy logic forecasts without modification and modification can be seen in Fig-7.

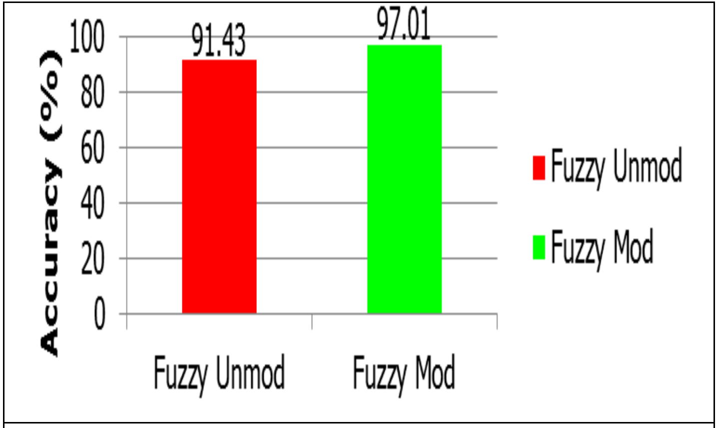

Fig-7: Comparison of Sectoral Accuracy Against RUPTL

Based on Fig-7, forecasts with modified fuzzy logic produce 97,01% accurate results than unmodified forecasts which are only 91,43%. With these results, the modified fuzzy logic improves the combined sectoral forecast accuracy to 5,58%. The combined accuracy of the forecasts of all sectors against the RUPTL has difference only 0,21% compared to the overall fuzzy logic forecast accuracy with 97,22% (look at Fig-5). This proves that the overall or sectoral forecasting approach will produce similar results.

CONCLUSION

Modifications that made in this study can reduce the total amount of fuzzy rules used and have a better forecasting ability than forecasting using unmodified fuzzy logic. The validation carried out on the historical data of 2010-2019 and the actual data of 2020 resulted in an average error of 13,63% and 17,04%, respectively. The accuracy of the forecast results against RUPTL until 2028 is 97,22% for the overall forecast and 97,01% for the combined sectoral forecast, 10,87% and 5,58% respectively better than unmodified fuzzy logic. Difference between the combined sectoral and overall forecast against the RUPTL is 0,21%, implies that the overall or sectoral forecasting approach will produce similar results. Accuracy of forecast results in 2029 and 2030 are not yet known because at the time of this study done, PLN has not issued RUPTL for forecasts until 2030.

REFERENCES

1. Ali, D., Yohanna, M., Puwu, M. I., & Garkida, B. M. (2016). Long-term load forecast modelling using a fuzzy logic approach. *Pacific Science Review A: Natural Science and Engineering*, *18*(2), 123-127.
2. Ali, A. T., Tayeb, E. B., & Shamseldin, Z. M. (2016). Short term electrical load forecasting using fuzzy logic. *International Journal of Advancement in Engineering Technology, Management and Applied Science*, *3*(11), 131-138.

3. AZIMJONOV, J., SELVİ, İ. H., & ÖZBEK, U. (2016). Evaluation of distance learning students performance using fuzzy logic. *Yönetim Bilişim Sistemleri Dergisi*, *2*(2), 87-97.
4. BPS Provinsi Banten. (2021). Provinsi Banten Dalam Angka 2011-2021. BPS Provinsi Banten.
5. Ding, S., Hipel, K. W., & Dang, Y. G. (2018). Forecasting China's electricity consumption using a new grey prediction model. *Energy*, *149*, 314-328.
6. Hammad, M. A., Jereb, B., Rosi, B., & Dragan, D. (2020). Methods and models for electric load forecasting: a comprehensive review. *Logistics, Supply Chain, Sustainability and Global Challenges*, *11*(1), 51-76.
7. Ahmad, A. M., & Sadikin, M. (2018). Comparison methods of short term electrical load forecasting. In *MATEC Web of Conferences* (Vol. 218, p. 01002). EDP Sciences.
8. Hawksworth, J., Clarry, R., & Audino, H. (2017). *The Long View How Will the Global Economic Order Change by 2050*. PricewaterhouseCoopers.
9. Jain, R., Jain, N., Gupta, Y., Chugh, T., Chugh, T., & Hemanth, D. J. (2020). A modified fuzzy logic relation-based approach for electricity consumption forecasting in India. *International Journal of Fuzzy Systems*, *22*(2), 461-475.
10. Singla, M. K., & Hans, S. (2018). Load forecasting using fuzzy logic tool box. *Global Research and Development Journal for Engineering*, *38*, 12-19.
11. Maspiyanti, F., Fanany, I., & Arymurthy, A. M. (2013). Klasifikasi Fase Pertumbuhan Padi Berdasarkan Citra Hiperspektral dengan Modifikasi Logika Fuzzy (Paddy Growth Stages Classification Based on Hyperspectral Image Using Modified Fuzzy Logic). *Jurnal Penginderaan Jauh dan Pengolahan Data Citra Digital*, *100*(1).
12. PT. Perusahaan Listrik Negara. (2019). *Rencana Usaha Penyediaan Tenaga Listrik PT. PLN (Persero) 2019-2028*. Direktorat Jenderal Ketenagalistrikan Kementerian Energi dan Sumber Daya Mineral.
13. Purwanto, S., & Suharyadi, S. (2016). *Statistika untuk Ekonomi dan Keuangan Modern* (3rd ed.). Salemba Empat.
14. Torrini, F. C., Souza, R. C., Oliveira, F. L. C., & Pessanha, J. F. M. (2016). Long term electricity consumption forecast in Brazil: a fuzzy logic approach. *Socio-Economic Planning Sciences*, *54*, 18-27.
15. Vivas, E., Allende-Cid, H., & Salas, R. (2020). A systematic review of statistical and machine learning methods for electrical power forecasting with reported mape score. *Entropy*, *22*(12), 1412.
16. Wardoyo, R., & Yuniarti, W. D. (2020). Analysis of Fuzzy Logic Modification for Student Assessment in e-Learning. *IJID (International Journal on Informatics for Development)*, *9*(1), 29-36.