BAREKENG: Journal of Mathematics and Its Applications
September 2025 Volume 19 Issue 3 Page 1699-1710
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol19iss3pp1699-1710

PREDICTION OF ECONOMIC GROWTH RATE OF TUBAN REGENCY WITH ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM ALGORITHM

Maya Muaziza[1*], Ahmad Zaenal Arifin[2], Suzatmo Putro[3]

[1,2]Mathematics Study Program, Faculty of Mathematics and Natural Sciences, Universitas PGRI Ronggolawe
Jln. Manunggal No.61, Gedongombo, Tuban, Jawa Timur, 62318, Indonesia
[3]Central Buerau Statistics of Tuban
Jln. Manunggal No. 8 Sukolilo, Panyuran, Tuban, Jawa Timur, 62318, Indonesia

Corresponding author's e-mail: * **mayamuaziza02@gmail.com**

ABSTRACT

Article History:

Received: 5th February 2025
Revised: 9th February 2025
Accepted: 12th March 2025
Published: 1st July 2025

Keywords:

Adaptive Neuro Fuzzy Inference System;
Economic Growth;
Fuzzy;
Prediction.

This research aims to implement and evaluate the accuracy of the Adaptive Neuro Fuzzy Inference System (ANFIS) forward stage method to predict the economic growth rate of the Tuban Regency. In the application of ANFIS, two types of variables are required, namely, input variables which include road length, the number of electricity customers, the number of health workers, the number of high schools, and the number of cases of ordinary theft. Meanwhile, the predicted output variable is the economic growth rate. The fuzzification process uses a triangular membership function to map the input values. The data used in this study were obtained from the Central Bureau of Statistics (BPS) of Tuban Regency for 2014-2024. The prediction results show a very low Mean Absolute Percentage Error (MAPE) value of 0.14%, which reflects a very high level of accuracy. With MAPE < 10%, the accuracy of this model reaches 99.86% based on calculations made through the Matlab GUI. This research shows that the Adaptive Neuro Fuzzy Inference System (ANFIS) method can be used effectively and accurately to predict the economic growth rate of the Tuban Regency.

How to cite this article:

M. Muaziza, A. Z. Arifin and S. Putro., "PREDICTION OF ECONOMIC GROWTH RATE OF TUBAN REGENCY WITH ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM ALGORITHM," BAREKENG*: J. Math. & App.*, vol. 19, no. 3, pp. 1699-1710, September, 2025.

Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*

Research Article · Open Access

1. INTRODUCTION

Economic growth is a key indicator that reflects the performance of a region in managing resources and improving the community's welfare. The economic structure of Tuban Regency is dominated by the Processing Industry business sector at 30.69% [1], supported by strategic infrastructure development such as roads and electricity. This infrastructure plays an important role as a catalyst for regional economic growth [2].

According to Mankiw [3], infrastructure in economics is a form of public capital formed from investments made by the government, which includes roads, bridges, and sewer systems. Complementing the above opinion, Bank [4] has provided limitations on infrastructure. Infrastructure is divided into three parts. First, economic infrastructure in the form of public utilities (electricity, telecommunications, sanitation, and gas), public works (roads, dams, bridges, irrigation, and drainage), and the transportation sector (railways, bus terminals, and airports). Second, social infrastructure such as education, health, housing, and recreation. Third, administrative infrastructure in the form of law enforcement, administrative control, and coordination.

Thus, we can predict the rate of economic growth based on economic infrastructure, social infrastructure, and administrative infrastructure. Economic infrastructure, such as road length and electricity subscribers, supports distribution and productivity. Social infrastructure, such as health workers and secondary schools, improves labor productivity and skills development. Administrative infrastructure, reflected by petty theft rates, indicates security concerns that may discourage investment. These interconnected factors create an environment conducive to growth. In previous research, Susano et al. have conducted research on predicting economic growth using the Fuzzy Inference System (FIS) Mamdani method using economic and social infrastructure input variables, which resulted in an accuracy value of 93.69% [5]. To produce better predictions, research is needed using other methods.

Adaptive Neuro Fuzzy Inference System is a method that utilizes artificial neural networks to apply fuzzy logic [6]. ANFIS uses adaptive learning to adjust fuzzy parameters to the given data, thus being able to handle uncertainty and variability in the data. In previous research, ANFIS has been used in various prediction applications, including air quality prediction, energy consumption, and industrial process control. For example, research about the Application of Adaptive Neuro Fuzzy Inference System Method (ANFIS) in predicting the Highest Price of Shares obtained an accuracy value of 97.8% [7], 98% [8], and 99% [9]. Implementation of the Mamdani Fuzzy Logic Method in Predicting Short-Term Electric Power Needs at Pt. PLN (Persero) Pematang Siantar with LOM defuzzification produces a MAPE value of 7.13%, which means the accuracy value is 92.87% [10], while Daily Peak Load Forecasting at Pt. PLN (Persero) Apb Central Java and DIY Using ANFIS (Adaptive Neuro-Fuzzy Inference System) with a MAPE value of 1.879% which means the accuracy value is 98.121% [11], Comparison of Classical Calculation Methods With Fuzzy Logic (Mamdani and Sugeno) on the Calculation of the Best Student Election the sugeno method is closer to the value of the flashlight data with percentage of 58.2% and mamdani 41.7% [12] while Predicting the Results of the Competency Test for Doctor Professional Program Students (UKMPPD) with ANFIS Approach with a MAPE value of 0.07% which means the accuracy value is 99.93% [13] , and Prediction of tensile strength in fused deposition modeling process using artificial neural network and fuzzy logic, using a fuzzy logic model produces a MAPE value of 3.29% which means the accuracy value is 96,71% [14] while Prediction of Tensile and Bending Strength of TKKS Fiber Composites Using the Adaptive Neuro-Fuzzy Inference System (ANFIS) Method with a MAPE value of 2.879% which means the accuracy value is 97.103% [15]. This shows that ANFIS is effective in predicting, with a low error rate and higher precision than fuzzy logic methods.

Matlab is a software that is often used in computational-based modeling and simulations [16], including in the implementation of ANFIS. Matlab provides various tools and functions that support the learning process, parameter optimization, and visualization of prediction results more efficiently. One of its key features is the Graphical User Interface (GUI), which allows users to implement and test ANFIS models. Matlab 2013R, as one of the stable versions, comes with ANFIS integration features for more accurate data analysis and decision making. By using the anfisedit command in the Command Window, users can directly edit and customize the ANFIS model by modifying the parameters and fuzzy rule structure. The identification process can then proceed using the Matlab GUI to visualize the results, making it easier for users to train and test the ANFIS model. This combination of ANFIS and Matlab GUI simplifies the modeling process, providing a flexible and accessible platform for both novice and advanced users. Previous research has shown that the application of GUI in fuzzy systems can enhance the effectiveness and accuracy of predictions. For instance, a study [17], which used ANFIS to monitor air quality in Surabaya, demonstrated that the integration of a GUI can help users manage data and better understand the prediction results.

Therefore, it is hoped that research on predicting the rate of economic growth using the Adaptive Neuro Fuzzy Inference System method and using Matlab 2013R assistance in the calculation process can help policymakers make more precise and effective decisions.

2. RESEARCH METHODS

This research uses a quantitative approach by using secondary data in the form of numbers obtained from the official publication of the Central Bureau of Statistics (BPS) of Tuban Regency. Data collection was conducted through literature studies by accessing literature available in the library and utilizing information from the official website of BPS Tuban Regency for 2014-2024. In applying the Adaptive Neuro Fuzzy Inference System method, this study included 6 variables, consisting of 1 output variable and 5 input variables. The input variables include road length, with 4 linguistic values, as well as the number of electricians, health workers, high schools, and many cases of ordinary theft, each of which is represented by 3 linguistic values. The ANFIS process uses a triangular membership function in the fuzzification process, while the fuzzy inference process uses the Sugeno method to combine the fuzzy rules that have been formed, resulting in a more precise and accurate output in making predictions. To evaluate the accuracy of the model, this research also calculates the prediction error rate using Mean Absolute Percentage Error (MAPE), which will indicate how close the prediction results are to the actual value described in section 2.2.

2.1 Adaptive Neuro-Fuzzy Inference System

Adaptive Neuro Fuzzy Inference (ANFIS) is a unification of fuzzy inference system (FIS) mechanisms, which are then described in an Artificial Neural Network (ANN) architecture [18].

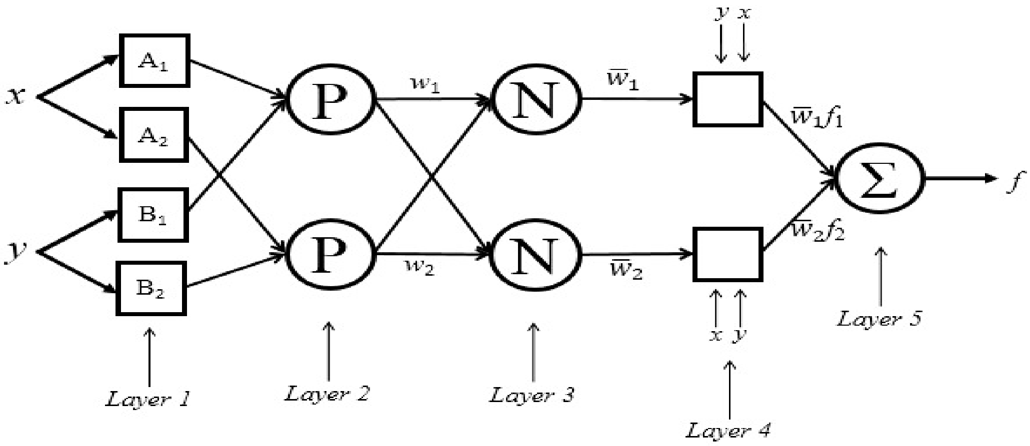

Figure 1. **ANFIS Structure**

There are 2 inputs and 1 output in the ANFIS structure shown in **Figure 1** above. In the structure, there are two types of nodes, namely adaptive (box) and non-adaptive (circle) nodes. ANFIS has a 5-layer structure, which can be explained as follows [19].

2.1.1 Layer 1

In layer 1, the fuzzification process occurs, in this study using a triangular membership function. It is defined by three parameters for defining three points: a and c for feet, and b for the tip of the curve [20]:

$$\mu(x) = \begin{cases} 0, & x \le a \text{ and } x > b \\ \dfrac{x-a}{c-a}, & a < x \le c \\ \dfrac{b-x}{b-c}, & c < x \le b \end{cases} \tag{1}$$

$$O_{1.i} = \mu_{A_i}(x),\ i = 1, 2, \ldots \text{ or } O_{1.i} = \mu_{B_i}(y),\ i = 1, 2, \ldots$$

With x and y are inputs at i^{th} neuron, A_i or B_i is the membership function of each i^{th} neuron. The output in layer 1 is the degree of membership given by the membership function of the input, namely $\mu_{A_1}(x)$, $\mu_{B_1}(y)$, $\mu_{A_2}(x)$, and $\mu_{B_2}(y)$.

2.1.2 Layer 2

Each node in this layer is labeled P with an output that is the result of multiplying the degree of membership generated from layer 1 by a function:

$$O_{2.i} = w \cdot i = \mu_{A_i}(x) \times \mu_{B_i}(y), i = 1, 2, \ldots \tag{2}$$

Each node output expresses the firing strength of each fuzzy rule. This function can be expanded if the premise part has more than two fuzzy sets. The number of nodes in this layer indicates the number of rules formed.

2.1.3 Layer 3

Each node in this layer is given the label N. The i^{th} neuron is used to calculate the power comparison against the sum of all weights:

$$O_{3.i} = \overline{W_i} = \frac{w_i}{w_1 + w_2}, i = 1,2, \ldots \tag{3}$$

Output in the form of normalized firing strength. If more than two rules are formed, the function can be expanded by dividing w_i by the total sum of w for all rules.

2.1.4 Layer 4

Each i^{th} neuron in this layer is an adaptive node with a function node:

$$O_{4.i} = \overline{W_i}\, f_i = \overline{W_i}(p_i x + q_i y + r_i) \tag{4}$$

The parameter of each layer is called the consequent parameters [21]. Where w_i is the normalized firing strength from layer 3, and the parameters p_i, q_i, r_i represent the adaptive consequent parameters.

$$y = f_i = p_i x + q_i y + r_i c \tag{5}$$

or in matrix form can be written as

$$y = AK. \tag{6}$$

It will be estimated using the Least Squares Estimator (LSE) in Sugeno fuzzy with output in the form of defuzzification. The matrix A is the design matrix obtained by multiplying the output from layer 3 with the input data. The entries in each column of this matrix are calculated using the following formula.

$$a_{i1} = O_{3,1} \times x_i \tag{7}$$

$$a_{i2} = O_{3,1} \times y_i \tag{8}$$

$$a_{i3} = O_{3,1} \tag{9}$$

$$a_{i4} = O_{3,2} \times x_i \tag{10}$$

$$a_{i5} = O_{3,2} \times y_i \tag{11}$$

$$a_{i6} = O_{3,2} \tag{12}$$

2.1.5 Layer 5

Each node in this layer is given the label Σ and there is only one fixed node that serves to sum all the inputs. Node function:

$$O_{5.i} = \sum \overline{W_i}\, f_i \tag{13}$$

This layer outputs the predicted value.

2.2 MAPE

MAPE (Mean Absolute Percentage Error) measures the prediction error as a percentage, with the formula [22]:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \tag{14}$$

where: y_i = Actual value

$\hat{y}_i$ = Predicted value

n = Length of the data

The level of forecasting accuracy can be seen in **Table 1 [23].**

Table 1. MAPE Value as a Forecasting Accuracy Level

Percentage MAPE	Accuracy Level
< 10%	High Forecasting Accuracy
10% - 20%	Good Forecasting Accuracy
>20% - 50%	Regular Forecasting Accuracy
> 50%	Inaccurate forecasting

3. RESULTS AND DISCUSSION

3.1 Data Set

The data used are road length (PJ), the number of electricity customers (TL), the number of health workers (TK), the number of high schools (SMA), the number of cases of ordinary theft (PB), and the economic growth rate (PE). The data used from 2013 to 2023, so that a total of 11 rows of data can be seen in **Table 2**.

Table 2. Data Set

Year	PJ	TL	TK	SMA	PB	PE
2013	901,931	153,501	625	93	33	5.84
2014	901,931	162,799	547	100	24	5.47
2015	901,931	174,113	656	105	22	4.89
2016	925,621	182,680	635	114	27	4.90
2017	925,621	192,621	795	116	23	4.98
2018	925,621	201,611	829	121	33	5.15
2019	926,351	310,447	857	122	17	5.14
2020	926,351	324,706	879	124	27	-5.85
2021	926,351	339,290	900	126	54	3.00
2022	893,640	335,173	2,513	129	39	8.88
2023	893,640	388,513	2,682	131	21	4.36

Source: Central Bureau of Statistics (BPS) of Tuban Regency [24]-[34]

3.2 Membership Function Graph

Based on the data in **Table 2**, the universe of discourse for each input variable can be determined. To determine the range in a fuzzy logic system, by identifying the universe of discourse (UOD) for each input variable, which is the range of possible values for that variable **[35]**. This range is then divided into several categories, and sets value limits for each category based on existing data or rules, thus resulting in **Table 3**.

Table 3. Speaker Universe for Every Input Variable

Variable	Speaker Universe	Linguistic Value	Range
Road Length	[893.640– 926.351]	Severely Damaged	[882,700 – 904,500]
		Broken	[893,600 – 915,400]
		Medium	[904,500 – 926,400]
		Both	[915,400 – 937,300]
Electricity Customers	[153.501– 388.513]	Low	[36,000 – 271,000]
		Medium	[153,500 – 388,500]
		High	[271,000 – 506,000]
Health Workers	[547 – 2682]	Low	[520 – 1,615]
		Medium	[547 – 2,682]
		High	[1,614 – 3,750]
High School	[93 – 131]	Low	[74 - 112]
		Medium	[93 - 131]
		High	[112 - 150]
Ordinary Theft	[17 – 54]	Low	[0 - 35]
		Medium	[17 - 54]
		High	[35-72]

Based on **Table 3**, the 5 input variables were formed. There are 16 neurons in layer 1, 324 neurons in layer 2, 324 neurons in layer 3, 324 neurons in layer 4, and 1 neuron in layer 5. Layers 2, 3, and 4 are obtained from a scale of 4×3^4. The formed ANFIS structure can be seen in **Figure 2**.

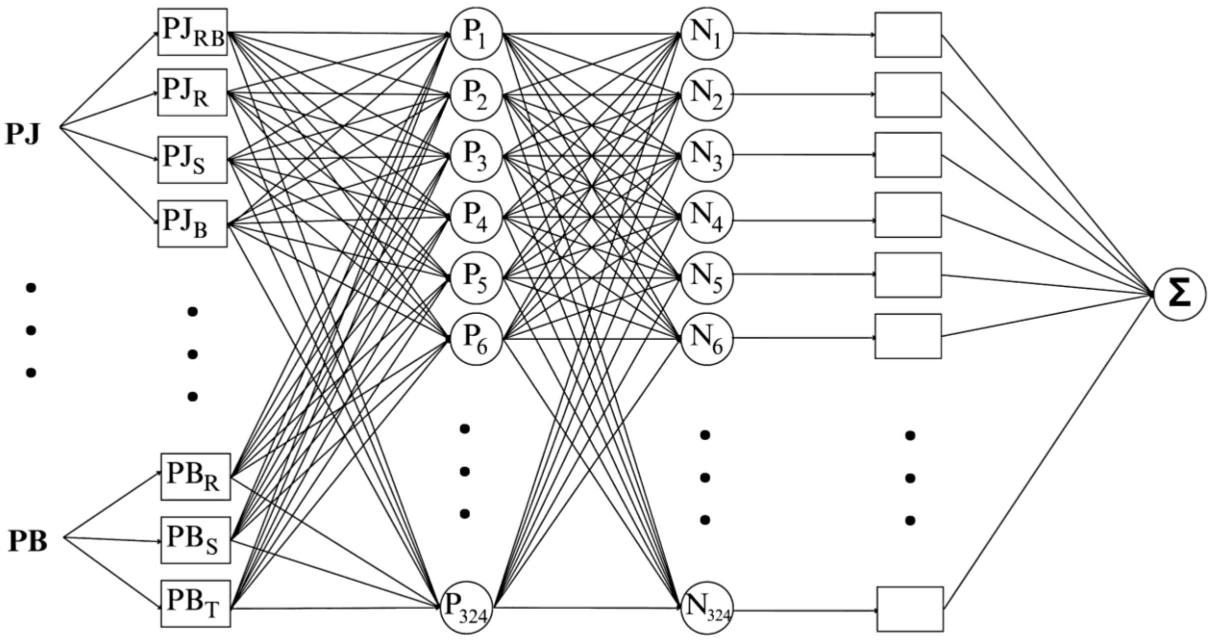

Figure 2. ANFIS Structure Formed

3.3 Manual Calculation

3.3.1 Layer 1

In layer 1, the fuzzification process occurs using **Equation (1)** on each input variable.

Length of severely damaged road

$$\mu_{PJ_{RB}}(x) = \begin{cases} 1, & x \leq 882{,}700 \\ \dfrac{904{,}500 - x}{904{,}500 - 882{,}700}, & 882{,}700 < x \leq 904{,}500 \\ 0, & x > 904{,}500 \end{cases}$$

Length of Damaged Road

$$\mu_{PJ_R}(x) = \begin{cases} 0, & x \leq 893{,}600 \ and \ x > 926{,}400 \\ \dfrac{915{,}400 - x}{915{,}400 - 893{,}600}, & 893{,}600 < x \leq 915{,}400 \\ \dfrac{926{,}400 - x}{926{,}400 - 915{,}400}, & 915{,}400 < x \leq 926{,}400 \end{cases}$$

Medium Road Length

$$\mu_{PJ_S}(x) = \begin{cases} 0, & x \leq 904{,}500 \ and \ x > 937{,}300 \\ \dfrac{x - 904{,}500}{915{,}400 - 926{,}400}, & 904{,}500 < x \leq 926{,}400 \\ \dfrac{937{,}300 - x}{937{,}300 - 926{,}400}, & 926{,}400 < x \leq 937{,}300 \end{cases}$$

$$\vdots$$

The number of thefts is usually high

$$\mu_{PB_T}(x) = \begin{cases} 0, & x \leq 35 \\ \dfrac{x - 35}{72 - 35}, & 35 < x \leq 72 \\ 1, & x > 72 \end{cases}$$

Based on the above equations, the membership degree of each data can be known, and then obtained.

$$\mu_{PJ_{RB}}(901{,}931) = \frac{904{,}500 - 901{,}931}{904{,}500 - 882{,}700} = \frac{2{,}569}{21{,}800} = 0.12$$

$$\mu_{PJ_R}(901{,}931) = \frac{915{,}400 - 901{,}931}{915{,}400 - 893{,}600} = \frac{13{,}469}{21{,}800} = 0.62$$

$$\mu_{PJ_S}(901{,}931) = 0$$

$$\vdots$$

$$\mu_{PB_T}(33) = 0$$

Based on the above calculations, the output layer 1 is obtained in **Table 4**.

Table 4. Output Layer 1

	1	2	…	11
$\mu_{PJ_{RB}}$	0.12	0.12	…	0.50
μ_{PJ_B}	0.62	0.62	…	1
μ_{PJ_S}	0	0		0
…	….	…	…	…
μ_{PB_T}	0	0	…	0

3.3.2 Layer 2

In layer 2, the fuzzy rule process is carried out using **Equation (2)**, and then obtained.

$$W_1 = \mu_{PJ_{RB}} \cdot \mu_{TL_R} \cdot \mu_{TK_R} \cdot \mu_{SMA_R} \cdot \mu_{PB_R} = 0.00162$$

$$W_2 = \mu_{PJ_{RB}} \cdot \mu_{TL_R} \cdot \mu_{TK_R} \cdot \mu_{SMA_R} \cdot \mu_{PB_S} = 0.01539$$

$$W_3 = \mu_{PJ_{RB}} \cdot \mu_{TL_R} \cdot \mu_{TK_R} \cdot \mu_{SMA_R} \cdot \mu_{PB_T} = 0$$

$$\vdots$$

$$W_{324} = \mu_{PJ_B} \cdot \mu_{TL_T} \cdot \mu_{TK_T} \cdot \mu_{SMA_T} \cdot \mu_{PB_T} = 0$$

Based on the above calculations, the output layer 2 is obtained as in **Table 5**.

Table 5. Output Layer 2

	W_1	W_2	...	W_{324}
1	0.00162	0.01539	…	0
2	0.005366	0.01402	…	0
3	0.003235	0.00751	…	0
...	…	…	…	…
11	0	0	…	0

3.3.3 Layer 3

In layer 3, the normalization process is carried out using **Equation (3)**, and then obtained.

$$\overline{W_1} = \frac{W_1}{W_1 + W_2 + W_3 + \cdots + W_{324}} = 0.001275$$

$$\overline{W_2} = \frac{W_2}{W_1 + W_2 + W_3 + \cdots + W_{324}} = 0.012115$$

$$\overline{W_3} = \frac{W_3}{W_1 + W_2 + W_3 + \cdots + W_{324}} = 0$$

$$\vdots$$

$$\overline{W_{324}} = \frac{W_{324}}{W_1 + W_2 + W_3 + \cdots + W_{324}} = 0$$

Based on the above calculations, the output layer 3 is obtained as in **Table 6**.

Table 6. Output Layer 3

	$\overline{W_1}$	$\overline{W_2}$	...	$\overline{W_{324}}$
1	0.001275	0.012115	…	0
2	0.002774	0.007247	…	0
3	0.001101	0.00256	…	0
...	…	…	…	…
11	0	0	…	0

3.3.4 Layer 4

In layer 4, the defuzzification process occurs using **Equation (4)**, and then obtained.

$$\overline{W_1}.f_1 = 0.001275 \cdot 0.0715 = 9.11797 \times 10^{-05}$$

$$\overline{W_2}.f_2 = 0.012115 \cdot 0.2049 = 0.002482319$$

$$\overline{W_3}.f_3 = 0 \cdot 0 = 0$$

$$\vdots$$

$$\overline{W_{324}}.f_{324} = 0 \cdot 0 = 0$$

Based on the above calculations, the output layer 4 is obtained as in **Table 7**.

Table 7. Output Layer 4

	$\overline{W_1}f_1$	$\overline{W_2}f_2$	…	$\overline{W_{324}}f_{324}$
1	9.11797×10^{-05}	0.002482319	….	0
2	0.000198	0.001485	…	0
3	$7.87398\text{E} \times 10^{-05}$	0.000524478	…	0
...	…	…	…	…
11	0	0	…	0

3.3.5 Layer 5

In layer 5, in the form of a prediction output whose function is to add up all input signals using **Equation (13)**, then obtained.

$$\begin{aligned}\sum_{n=1}^{324} \overline{W_n}f_n &= \overline{W_1}f_1 + \overline{W_2}f_2 + \overline{W_3}f_3 + \cdots + \overline{W_{324}}f_{324} \\ &= 9.11797 \times 10^{-05} + 0.002482319 + 0 + \cdots + 0 \\ &= 5.84\end{aligned}$$

Based on the above calculations, the output layer 5 is obtained as in **Table 8**.

Table 8. Output Layer 5

Year	Predicted Economic Growth
2013	5.84
2014	5.47
2015	4.89
...	…
2023	4.36

3.4 Matlab GUI Calculation

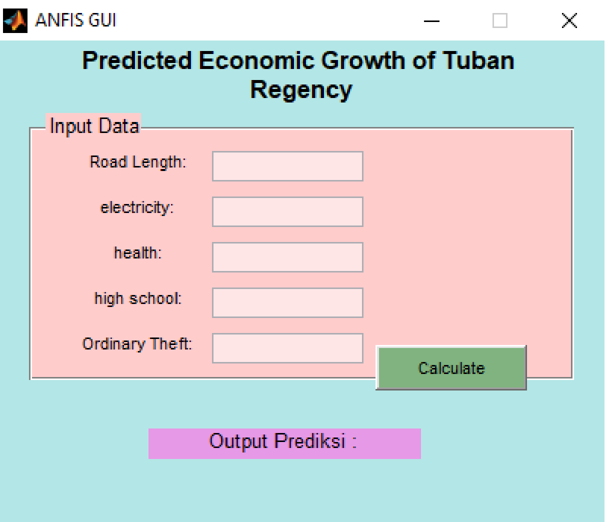

Figure 3. GUI Program View

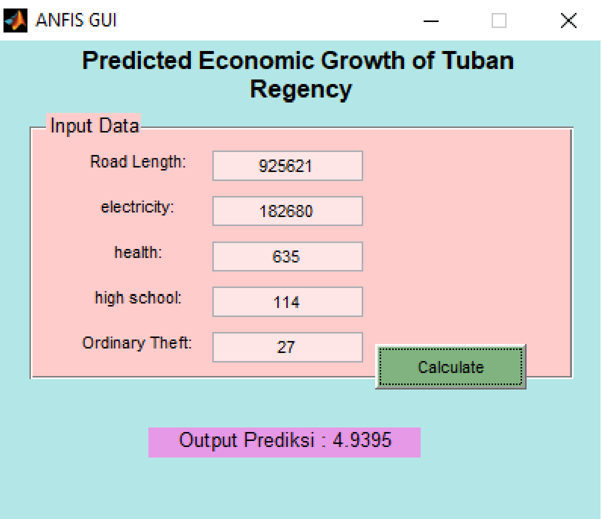

Figure 4. ANFIS Result View

Figure 3 shows the GUI program that is formed based on the fuzzy toolbox. In this GUI program, we will see how the output is produced in accordance with the input entered by entering a value in each input box. Next, click calculate, and the prediction results will appear in the output box. **Figure 4** shows the results of the 2016 data test.

3.5 Calculating Accuracy Value

Based on **Equation (14)**, the MAPE value obtained is shown in **Table 9**.

Table 9. **Prediction Result**

Actual Value	Manual Predicted Value	GUI Predicted Value
5.84	5.84	5.88
5.47	5.47	5.47
4.89	4.89	4.89
4.90	5.13	4.94
4.98	5.04	4.99
5.15	5.15	5.15
5.14	4.91	5.14
-5.85	-6.46	-6.08
3.00	3.00	3.00
8.88	8.78	8.71
4.36	4.36	4.43
MAPE	**1.99%**	**0.14%**

From the research results, it was found that the accuracy rate was very high, namely 98.01% in manual calculations and 99.86% in calculations using Matlab GUI. According to [36], a well-designed GUI can greatly improve the effectiveness of fuzzy systems by streamlining the user experience, reducing the potential for human error, and increasing the accessibility of complex analytical tools. The use of the GUI in this study has contributed to the high prediction accuracy. When compared to previous research done by Susano et al., which uses the Fuzzy Inference System (FIS) Mamdani with an accuracy rate of 93.69% [5], the prediction of economic growth using ANFIS has better results. One of the reasons is that the input variables used in this study are more complex, covering all infrastructure categories, namely: length of roads and the number of electricity customers represent economic infrastructure, the number of workers and the number high schools represent social infrastructure, and many cases of common theft represent administrative infrastructure. Both the Mamdani Fuzzy Inference System (FIS) and the Adaptive Neuro-Fuzzy Inference System (ANFIS) implement fuzzy logic concepts in a rule-based decision-making process. However, they differ in the way they work and their level of complexity.

Mamdani FIS applies a more conventional approach by relying on fuzzy rules that are manually designed by experts. This model uses membership functions as well as predefined if-then rules to process information and produce appropriate outputs [37]. While this approach is relatively simple and easy to interpret, its limitation lies in its inability to automatically adjust fuzzy rules based on empirical data, making it less flexible in handling datasets with complex patterns.

Meanwhile, ANFIS is a further development that implements fuzzy logic in Sugeno's FIS with an Artificial Neural Network (ANN) [38]. Unlike the Mamdani FIS, which produces output in the form of a fuzzy set and requires a defuzzification process, the Sugeno FIS used in ANFIS has a consequent in the form of a linear function or constant [39], so it can directly produce numerical output without requiring a defuzzification stage. This implementation allows ANFIS to automatically adjust and optimize fuzzy rules through a data-driven learning process. Thus, ANFIS has significant advantages in handling data with high complexity and improving prediction accuracy compared to the Mamdani FIS approach. Its ability to recognize and adaptively model non-linear patterns makes it more effective and efficient in producing more accurate predictions without the need for manual intervention in fuzzy rule generation.

4. CONCLUSIONS

It can be concluded from this study that the prediction of economic growth rate using an Adaptive Neuro Fuzzy Inference System with 5 input variables, namely, road length, the number of electricity customers, the number of health workers, the number of high schools, and the number of cases of ordinary theft and output variables of economic growth, with data sourced from the Central Bureau of Statistics (BPS) of Tuban Regency show an accuracy of 98.01% in manual calculations and 99.86% in calculations using the Matlab GUI. The MAPE is 1.99% in manual calculation and 0.14% in calculation using Matlab GUI. With MAPE < 10%, it shows that the Adaptive Neuro Fuzzy Inference System can be used as a prediction of economic growth rates.

Future research is recommended to include additional macroeconomic variables such as inflation, monetary policy, and international trade that have a more significant impact on economic growth and replace other membership functions other than triangular membership functions, or can use other methods such as SVM or neural networks, so as to improve predictions and increase model accuracy.

REFERENCES

[1] B. K. Tuban, “PERTUMBUHAN EKONOMI KABUPATEN TUBAN,” *Badan Pus. Stat. Kabupaten Tuban*, no. 04, pp. 1–12, 2023, [Online]. Available: https://tubankab.bps.go.id/pressrelease/2024/02/28/170/pertumbuhan-ekonomi-kabupaten-tuban-tahun-2023.html

[2] E. Wahyuanto, *MENAKAR KINERJA DAN PROFESI DOSEN*. Arta Media Nusantara, 2024.

[3] N. G. Mankiw, “GOVERNMENT DEBT AND CAPITAL ACCUMULATION IN AN ERA OF LOW INTEREST RATES,” *Brookings Pap. Econ. Act.*, vol. 2022, no. 1, pp. 219–231, 2022.

[4] W. Bank, *POVERTY AND SHARED PROSPERITY 2020: REVERSALS OF FORTUNE*. The World Bank, 2020.

[5] A. Susano, W. Anggraeni, and N. Kustian, “PREDIKSI PERTUMBUHAN EKONOMI DI PROVINSI BANTEN MENGGUNAKAN FUZZY INFERENCES SYSTEM (FIS) MAMDANI,” *Pros. Semin. Nas. Sains*, vol. 1, no. 1, pp. 681–695, 2020, [Online]. Available: http://proceeding.unindra.ac.id/index.php/sinasis/article/view/4084%0Ahttp://proceeding.unindra.ac.id/index.php/sinasis/article/download/4084/705

[6] A. Riski, W. N. Haqqi, and A. Kamsyakawuni, “RAINFALL PREDICTION IN JEMBER REGENCY WITH ADAPTIVE NEURO FUZZY INFERENCE SYSTEM BASED ON GSMAP SATELLITE DATA,” *BAREKENG J. Ilmu Mat. dan Terap.*, vol. 17, no. 3, pp. 1713–1724, 2023, doi: 10.30598/barekengvol17iss3pp1713-1724.

[7] I. P. S. Wijayaa, M. A. Raharjaa, L. A. A. R. Putria, I. P. G. Hendra, I. B. M. M. Suputraa, and I. G. S. Astawaa, “PENERAPAN METODE ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS) DENGAN MEMBERSHIP FUNCTION TIPE GAUSSIAN DAN GENERALIZED BELL DALAM PREDIKSI HARGA TERTINGGI SAHAM,” *J. Elektron. Ilmu Komput. Udayana p-ISSN*, vol. 2301, p. 5373, 2022.

[8] Y. E. A. Seputra and M. Meirinaldi, “PREDIKSI INDEKS GABUNGAN HARGA SAHAM (ISHG) MENGGUNAKAN ADAPTIVE NEURAL FUZZY INFERENCE SYSTEM (ANFIS),” *J. Ekon.*, vol. 22, no. 2, pp. 131–146, 2020.

[9] A. Damayanti and D. Agustina, “IMPLEMENTASI METODE ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS) DALAM PREDIKSI HARGA SAHAM X,” *Euler J. Ilm. Mat. Sains dan Teknol.*, vol. 12, no. 1, pp. 71–76, 2024.

[10] R. Dinur, “IMPLEMENTASI METODE FUZZY LOGIC MAMDANI DALAM MEMPREDIKSI KEBUTUHAN DAYA LISTRIK JANGKA PENDEK DI PT. PLN (PERSERO) PEMATANG SIANTAR,” *Tek. Inform. dan Tek. Elektro*, vol. 5, no. 1, pp. 21–26, 2019.

[11] M. Susanti, S. Handoko, and B. Winardi, “PERAMALAN BEBAN PUNCAK HARIAN PADA PT. PLN (PERSERO) APB JATENG DAN DIY MENGGUNAKAN ANFIS (ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM),” *Transient J. Ilm. Tek. Elektro*, vol. 5, no. 3, pp. 255–261, 2017.

[12] A. Wantoro, “KOMPARASI PERHITUNGAN PEMILIHAN MAHASISWA TERBAIK MENGGUNAKAN METODE PERHITUNGAN KLASIK DENGAN LOGIKA FUZZY MAMDANI & SUGENO,” *J. Pendidik. Teknol. Dan Kejuru.*, vol. 15, no. 1, 2018.

[13] F. M. Siregar, G. W. Nurcahyo, and S. Defit, “PREDIKSI HASIL UJIAN KOMPETENSI MAHASISWA PROGRAM PROFESI DOKTER (UKMPPD) DENGAN PENDEKATAN ANFIS,” *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 2, no. 2, pp. 554–559, 2018.

[14] A. D. Tura, H. G. Lemu, H. B. Mamo, and A. J. Santhosh, “PREDICTION OF TENSILE STRENGTH IN FUSED DEPOSITION MODELING PROCESS USING ARTIFICIAL NEURAL NETWORK AND FUZZY LOGIC,” *Prog. Addit. Manuf.*, vol. 8, no. 3, pp. 529–539, 2023.

[15] A. Gani and A. Mujianto, “PREDIKSI KEKUATAN TARIK DAN BENDING KOMPOSIT SERAT TKKS MENGGUNAKAN ARTIFICIAL NEURO FAZZY INFERENCE SYSTEM (ANFIS),” vol. 3, no. 1, pp. 103–110, 2024.

[16] A. M. de Almeida, M. K. Lenzi, and E. K. Lenzi, “A SURVEY OF FRACTIONAL ORDER CALCULUS APPLICATIONS OF MULTIPLE-INPUT, MULTIPLE-OUTPUT (MIMO) PROCESS CONTROL,” *Fractal Fract.*, vol. 4, no. 2, p. 22, 2020.

[17] S. A. N. Gupita, A. S. Aisjah, and S. Arifin, “PREDIKSI KADAR POLUTAN MENGGUNAKAN ADAPTIVE NEOURO-FUZZY INFERENCE SYSTEM (ANFIS) UNTUK PEMANTAUAN KUALITAS UDARA DI KOTA SURABAYA,” *Surabaya Dep. Tek. Fis. Fak. Teknol. Ind. Inst. Teknol. Sepuluh Novemb.*, 2017.

[18] U. Hani’ah, R. Arifudin, and E. Sugiharti, “IMPLEMENTASI ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) UNTUK PERAMALAN PEMAKAIAN AIR DI PERUSAHAAN DAERAH AIR MINUM TIRTA MOEDAL SEMARANG,” *Sci. J. Informatics*, vol. 3, no. 1, pp. 76–87, 2016.

[19] U. Khasanah, D. C. R. Novitasari, and W. D. Utami, “ANALISIS PERAMALAN BEBAN LISTRIK JANGKA PENDEK MENGGUNAKAN METODE ADAPTIVE NEURO FUZZY INFERENCE SYSTEM: STUDI KASUS PT. PLN (PERSERO) AREA PENGATURAN DISTRIBUSI JAWA TIMUR,” *J. Mat.*, vol. 1, no. 1, pp. 17–24, 2019.

[20] N. Talpur, M. N. M. Salleh, and K. Hussain, “AN INVESTIGATION OF MEMBERSHIP FUNCTIONS ON PERFORMANCE OF ANFIS FOR SOLVING CLASSIFICATION PROBLEMS,” in *IOP conference series: materials science and engineering*, 2017, vol. 226, no. 1, p. 12103.

[21] G. D. Santika, W. F. Mahmudy, and A. Naba, “ELECTRICAL LOAD FORECASTING USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM,” *Int. J. Adv. Soft Comput. Appl*, vol. 9, no. 1, pp. 50–69, 2017.

[22] L. Chen, T. Wu, Z. Wang, X. Lin, and Y. Cai, “A NOVEL HYBRID BPNN MODEL BASED ON ADAPTIVE EVOLUTIONARY ARTIFICIAL BEE COLONY ALGORITHM FOR WATER QUALITY INDEX PREDICTION,” *Ecol. Indic.*, vol. 146, p. 109882, 2023.

[23] A. Kamsyakawuni, W. Sholihah, and A. Riski, “PREDICTION SYSTEM FOR THE AMOUNT OF SUGAR PRODUCTION USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM,” *BAREKENG*, vol. 18, no. 4, pp. 2597–

2610, 2024, https://doi.org/10.30598/barekengvol18iss4pp2597-2610.
[24] B. K. Tuban, *KABUPATEN TUBAN DALAM ANGKA 2014*. Tuban: BPS Kabupaten Tuban, 2014.
[25] B. K. Tuban, *KABUPATEN TUBAN DALAM ANGKA 2015*. Tuban: BPS Kabupaten Tuban, 2015.
[26] B. K. Tuban, *KABUPATEN TUBAN DALAM ANGKA 2024*. Tuban: BPS Kabupaten Tuban, 2024.
[27] B. K. Tuban, *KABUPATEN TUBAN DALAM ANGKA 2016*. Tuban: BPS Kabupaten Tuban, 2016.
[28] B. K. Tuban, *KABUPATEN TUBAN DALAM ANGKA 2017*. Tuban: BPS Kabupaten Tuban, 2017.
[29] B. K. Tuban, *KABUPATEN TUBAN DALAM ANGKA 2018*. Tuban: BPS Kabupaten Tuban, 2018.
[30] B. K. Tuban, *KABUPATEN TUBAN DALAM ANGKA 2019*. Tuban: BPS Kabupaten Tuban, 2019.
[31] B. K. Tuban, *KABUPATEN TUBAN DALAM ANGKA 2020*. Tuban: BPS Kabupaten Tuban, 2020.
[32] B. K. Tuban, *KABUPATEN TUBAN DALAM ANGKA 2021*. Tuban: BPS Kabupaten Tuban, 2021.
[33] B. K. Tuban, *KABUPATEN TUBAN DALAM ANGKA 2022*. Tuban: BPS Kabupaten Tuban, 2022.
[34] B. K. Tuban, *KABUPATEN TUBAN DALAM ANGKA 2023*. Tuban: BPS Kabupaten Tuban, 2023.
[35] D. Gupta and A. K. Ahlawat, "TAXONOMY OF GUM AND USABILITY PREDICTION USING GUM MULTISTAGE FUZZY EXPERT SYSTEM.," *Int. Arab J. Inf. Technol.*, vol. 16, no. 3, pp. 357–363, 2019.
[36] M. Ashfaq, "A TRIBUTE TO FATHER OF FUZZY SET THEORY AND FUZZY LOGIC (Dr. Lotfi A. Zadeh)," *J. Swarm. Intel. Evol. Comput*, vol. 7, no. 2, 2018.
[37] E. F. Ma'rif and A. M. Abadi, "FUZZY APPLICATION (MAMDANI METHOD) IN DECISION-MAKING ON LED TV SELECTION," *BAREKENG J. Ilmu Mat. dan Terap.*, vol. 18, no. 2, pp. 1117–1128, 2024, https://doi.org/10.30598/barekengvol18iss2pp1117-1128.
[38] N. Walia, H. Singh, and A. Sharma, "ANFIS: ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM-A SURVEY," *Int. J. Comput. Appl.*, vol. 123, no. 13, 2015.
[39] M. Öztürk, "A MODIFIED ANFIS SYSTEM FOR AERIAL VEHICLES CONTROL," 2022.