Prediction of population growth using Sugeno and Adaptive Neuro-Fuzzy Inference System (ANFIS)

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Abstract. Government use population growth data to design sustainable policies frameworks. This research aims to predict the population growth using adaptive neuro-fuzzy inference system (ANFIS) and Sugeno as comparison method. The ANFIS consists of determining layers (1 to 5), system design, implementation, and system testing stage. The results of using ANFIS is 0.44% while prediction test of using Sugeno is 16.09% in year 2010. The Sugeno result is categorized as a negative growth since it is far up from the ideal rate set by the government of 0.5% per year.

1. Introduction
Indonesian government held the population census in every 10 years. Census data is the primary data, used by social, economic, and demographic planners. ANFIS (adaptive neural fuzzy inference system) combined the of fuzzy inference system and neural network adaptive learning ability, which used for optimization, data mining, selection multi criteria, and prediction [1-6].

The selection of the methods was taking based on previous works reported by Oprea et al. [4] who used ANFIS as an internal fuzzy rule base in a prediction. When rule base is empty, ANFIS generates the rules and adjust the FIS parameters to match the input output datasets. The results are compared with data mining technique and evaluated by RMSE, MAPE, and simulation time. ANFIS has a small value of RMSE which is indicates that ANFIS is better in prediction than another technique in this research. This is corroborated by Zhang and Lei [7] who reported that ANFIS convergence speed is faster and predictive values are in conformity with the measured values in the case of prediction of laser cutting roughness. In many cases, ANFIS are combined with several methods such as ANFIS-Genetic Algorithm, ANFIS-Differential evolution, ANFIS-particle swarm optimization [8]. ANFIS result is depend on selection of optimization method in training [5].

This research will predict the population growth using a computer based system. The method used in this research are Adaptive Neuro Fuzzy Inference System (ANFIS) to determine the prediction of growth rate of the inhabitants of the per year, where Sugeno [9, 10] is used as a baseline method. This research is designed to ease the government to predict the annual of population growth. The data retrieves from the Central Bureau of the Republic of Indonesia with population census period of 1961, 1971, 1980, 1990, 2000, 2010.
2. Method

2.1. Adaptive Neuro Fuzzy Inference System

Adaptive Neuro Fuzzy Inference System (ANFIS) is a combination of artificial neural networks and fuzzy logic. Fuzzy inference systems trained using artificial neural network systems. Thus, the hybrid possesses all advantages of artificial neural network systems and fuzzy inference systems. From its ability to learn, the neuro-fuzzy system is often referred as adaptive neuro fuzzy inference systems (ANFIS). One of the most well-known structures is the fuzzy inference of the Takagi-Sugeno-Kang model [9, 10], is shown in figure 1.

![ANFIS structure](image)

Figure 1. ANFIS structure.

In the Neuro-Fuzzy system, there are five layers of process fuzzification (1st Layer), production (2nd layer), normalization (3rd layer), defuzzification (4th layer), and summarization (5th layer) [10-12].

2.2. Sugeno methods

Fuzzy sugeno is a fuzzy inference technique which can be seen as the form of IF – THEN rules, where the output is a linear equation or constant values [9]. The Sugeno model uses the Singleton membership function that has a membership degree of 1 on a single crisp value and 0 on another crisp value [10].

a. Fuzzy Sugeno Orde-Zero

In general, the form of fuzzy model Sugeno Orde zero is shown in equation (1).

$$\text{IF } (X_1 \text{ is } A_1) o (X_2 \text{ is } A_2) o \ldots o (X_n \text{ is } A_n), \text{then } z = k$$

where $A_i$ is the set of fuzzy to-$i$ as antecedents and $k$ is a constant as a consequence.

b. Model Fuzzy Sugeno Orde-One

In general, the form of fuzzy model Sugeno Orde one is shown in equation (2).

$$\text{IF } (X_1 \text{ is } A_1) o (X_2 \text{ is } A_2) o \ldots o (X_n \text{ is } A_n) \text{ THEN } z = p_1 * X_1 + p_2 * X_2 + \ldots + p_N * X_n = q$$

where $A_i$ is the set of fuzzy to-$i$ as antecedents and $p_i$ is a constant to $i$ and $q$ is also a constant in consequence.

3. Results and discussion

3.1. ANFIS

The ANFIS of population growth in Sleman regency – Indonesia as data sample is shown in equation (3). Where $\mu A(x)$ is degree of membership, $x$ is population of census data, $c$ is standard deviation, $a$ is mean, and $y, z$ are census time.
\[
\mu_a(x) = \frac{1}{1+\left|\frac{x}{a}\right|^b}
\]  

(3)

Based on figure 1 can be describes the process for each layer. The first layer, fuzzy layer, converts inputs into a fuzzy set by means of membership functions (MFs). It contains adaptive nodes, that can be seen in table 1.

| Table 1. 1st layer. |
|---------------------|
| Data | Y | Z |
|------|---|---|
|      | X1 | X2 | X1 | X2 |
| 1    | 516.653 | 588.313 |
| 2    | 588.313 | 677.323 |
| 3    | 677.323 | 780.334 |
| 4    | 780.334 | 901.377 |
| 5    | 901.377 | 1,093,110 |
| Mean | 628,433.3 | 722,337.6 | 789,350 | 936,722 |
| Standard deviation | 64,272.2 | 76,043.2 | 79,215.0 | 110,583.0 |

From table 1. The fuzzy set by MFs can be find by using describe as \( \mu_A_1(x) = \frac{1}{1+\left|\frac{x-722337.6}{76043.2}\right|^b} \), \( \mu_A_2(x) = \frac{1}{1+\left|\frac{x-79215.0}{76043.2}\right|^b} \), \( \mu_B_1(x) = \frac{1}{1+\left|\frac{x-780.334}{76043.2}\right|^b} \), and \( \mu_B_2(x) = \frac{1}{1+\left|\frac{x-901.377}{76043.2}\right|^b} \). The result shows various forms of membership function for fuzzy set A. The parameters in this layer are called premise parameters which degree of its membership can be seen in table 2.

| Table 2. Degree of membership. |
|-------------------------------|
| Data | Degree of Membership |
|------|----------------------|
|      | \( \mu_{A_1} \) | \( \mu_{A_2} \) | \( \mu_{B_1} \) | \( \mu_{B_2} \) |
| 1    | 0.248465            | 0.243529            | 0.077817            | 0.091520            |
| 2    | 0.719602            | 0.740514            | 0.134395            | 0.153787            |
| 3    | 0.633468            | 0.632245            | 0.333333            | 0.333333            |
| 4    | 0.151846            | 0.152828            | 0.987211            | 0.907310            |
| 5    | 0.052537            | 0.040366            | 0.333333            | 0.333333            |

In the 2nd layer, every node is a fixed node, with the function node to be multiplied by input signals to serve as output signal as shown in equation (4).

\[
W_1 = \mu_{A_1}(x) \ast \mu_{B_1}(x); W_2 = \mu_{A_2}(x) \ast \mu_{B_2}(x)
\]  

(4)

where \( W_1 \) and \( W_2 \) are firing-strength. \( \mu_{A_1}(x) \) is degree of membership of set Y, \( \mu_{B_1}(x) \) is degree of membership of set Z. The 2nd layer results can be seen in table 3.

| Table 3. 2nd Layer result. |
|-----------------------------|
| Data | Output 2nd layer |
|------|------------------|
|      | \( w_1 \) | \( w_2 \) |
| 1    | 0.019335 | 0.022288 |
| 2    | 0.096711 | 0.113882 |
| 3    | 0.211156 | 0.210748 |
| 4    | 0.149904 | 0.138662 |
| 5    | 0.017512 | 0.013455 |
Every node in 3\textsuperscript{rd} layer is considered a fixed node, marked by a circle and labelled by $N$, with function node to normalize the firing strength by computing the ratio of the node firing strength to sum of all firing strength rules by using equation (5).

$$\bar{w} = \frac{w_1}{w_1 + w_2}; \quad \bar{w} = \frac{w_2}{w_1 + w_2}$$

where $\bar{w}$ is normalized firing strength, $w_1$ and $w_2$ are the output of 2\textsuperscript{nd} layer. The quantity $\bar{w}$ is known as the normalised firing strength. The output of 3\textsuperscript{rd} layer can be seen in table 4.

| Data | $\bar{w}_1$ | $\bar{w}_2$ |
|------|-------------|-------------|
| 1    | 0.464527    | 0.535473    |
| 2    | 0.459233    | 0.540767    |
| 3    | 0.500483    | 0.499517    |
| 4    | 0.519478    | 0.480522    |
| 5    | 0.565501    | 0.434499    |

The output of the parameter coefficients can be seen in table 5.

| Data | $p_1$ | $q_1$ | $r_1$ | $p_2$ | $q_2$ | $r_2$ |
|------|-------|-------|-------|-------|-------|-------|
| 1    | 0.929053 | 1.858106 | 0.464527 | 2.677367 | 13.386836 | 0.535473 |
| 2    | 0.918465 | 1.836931 | 0.459233 | 2.703837 | 13.519184 | 0.540767 |
| 3    | 1.000966 | 2.001932 | 0.500483 | 2.497585 | 12.487924 | 0.499517 |
| 4    | 1.038956 | 2.077913 | 0.519478 | 2.402609 | 12.013046 | 0.480522 |
| 5    | 1.131002 | 2.262003 | 0.565501 | 2.172496 | 10.862481 | 0.434499 |

In the 4\textsuperscript{th} layer, every node is an adjustable node, marked by a square, with node function as in equation (6).

$$o_{4,i} = \bar{w}_i \cdot f_i = \bar{w}_i (p_i x + q_i x + r_i)$$

where $p_i$, $q_i$, and $r_i$ are the parameters set, referred to as the consequent parameters.

The last process is finding $w_i$ and $y_i$ for summarization process, $y' = \Sigma \bar{w} y = \bar{w}_1 y_1 + \bar{w}_2 y_2$, in 5\textsuperscript{th} layer which can be shown in table 6.

| Data | $\bar{w}_1 y_1$ | $\bar{w}_2 y_2$ | $\Sigma \bar{w} y_1$ |
|------|----------------|----------------|-------------------|
| 1    | 10.822204      | 184.717673     | 195.539877        |
| 2    | 10.582174      | 188.275869     | 198.858043        |
| 3    | 12.523681      | 161.447750     | 173.971430        |
| 4    | 13.472641      | 149.786203     | 163.258845        |
| 5    | 15.915474      | 123.342183     | 139.257657        |

After finding the 5\textsuperscript{th} layer, the data will be processed under normal circumstances, thus we need to normalize it by using equation (7).
\[ \text{result} = \left( \frac{a_1}{L_5} \right) + a_1 \]  

(7)

where \( a_1 \) is population growth data, and \( L_5 \) is output of 5\textsuperscript{th} layer. The results of long-term population forecasts normalization which is conducted using ANFIS, then it compared with the actual data from 1961 to 2000 (table 7).

**Table 7.** Comparison results between real data of population and ANFIS.

| Data | Year | Population | ANFIS | Error |
|------|------|------------|-------|-------|
| 1    | 1961 | 516,653    | 519,295 | 0.51% |
| 2    | 1971 | 588,313    | 590,911 | 0.44% |
| 3    | 1980 | 677,323    | 680,292 | 0.44% |
| 4    | 1990 | 780,334    | 783,498 | 0.41% |
| 5    | 2000 | 901,377    | 905,087 | 0.41% |
| **Average** | | | | 0.44% |

### 3.2. Sugeno

In this research, Fuzzy Sugeno method will be used as a comparison. The steps of Sugeno method can be described as:

1) Establishment of membership for Increase function and decrease Function (figure 2).

![Figure 2. Decrease and Increase Degree of membership function.](image)

Degree of membership value from decrease function and increase function, can be calculated as \( \mu_{ptmbh} \) Decrease \([780334]\) = \( \frac{901377-780334}{224054} \) = 0.54, and \( \mu_{ptmbh} \) Increase \([780334]\) = \( \frac{780334-677323}{224054} \) = 0.46.

2) Establishment of membership for Few function and many Function (figure 3).

![Figure 3. Decrease and Increase Degree of membership function.](image)
Degree of membership value from few function and many function can be calculated as µptmbh Few [588313] = \frac{677323-598313}{160670} = 0.56, and µptmbh Many [588313] = \frac{588313-516653}{160670} = 0.44. Some possible rules which possible can be created by Sugeno for the experimental data, and the population created by Sugeno can be seen in table 8, and the error of prediction of Sugeno is 16.09% (higher than 3%).

| Real data population | Sugeno       |
|----------------------|--------------|
| 1,093,110            | 1,269,064    |

Based on the calculation of Sleman growth rate prediction, it can be said that there is a negative growth due to the occurrence of spike and increase of population equal to 16.09%. This result far from ideal rate which has been set by government which equal to 0.5% per year.

4. Conclusion
The result of population growth prediction is 0.44% from census data, while the prediction data of population growth using Sugeno method is 16.10%. Based on this result, the Sugeno method resulted in negative growth predictions, meaning that this result is far from the tolerance of government prediction that is only 0.5% per year.

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